EFFECTS OF SHOCKS ON ECONOMIC DEVELOPMENT AND ROLES OF RESILIENCE FACTORS

By

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ABSTRACT

In recent decades, the inability to quickly cope with shocks and stressors became perhaps the most serious threats to growth and development, and a matter of concern among development stakeholders. As a result, they are now prioritizing resilience building at individual, household, and community levels. By providing up to date analysis on key missing gaps, this dissertation contributes to the literature explaining the nexus between shocks, resilience, and development, and informs the policy-making process about mitigation of various shocks and stressors.

Departing from the usual practice of assessing the impacts of COVID-19 on development outcomes, the first essay investigates the effects of six policy responses to the COVID-19 pandemic on the farm and nonfarm incomes of agricultural households using Nigeria as a case study. The roles of endogenous policies such as lockdowns and stay at home orders have hitherto not been addressed in the literature. Essay 1 also examines the roles of factors that provide households with absorptive, adaptive, and transformative resilience capacities during unprecedented shocks. The results suggest that policies that tend to increase family labor availability were beneficial for agricultural households on the short run. In addition, the ability of agricultural households to withstand the adverse effects of the policy responses to the pandemic depends on their land size, wealth level, and degrees of income diversification, involvement in processing activities, and reliance on hired labor. These results suggest that policy responses to a health crisis, specifically containment measures, which are aimed at overall mitigation of adverse impacts, need to consider the impacts on farm viability. Since agriculture is crucial to livelihoods in developing countries, its role may be compromised if policies enacted do not consider the effects on the sector.

For sub-Saharan African (SSA) countries, the second essay examines the short- and long-term effects of conflicts and droughts on agricultural growth and transformation trajectories using partial and total factor productivities measures as indicators of these processes. It also introduces

an alternative approach to measuring resilience based on the timeframe in which the effects of a shock remain significant. The results suggest instantaneous and persistent disruptive effects of conflicts and droughts on the structure of agricultural production, which occur mainly through effects on quality and quantity of input use. Additionally, the overall structure of agricultural production is characterized by greater resilience to conflicts than droughts. By tying shocks to productivity, resilience and agricultural production in a temporal way, this study advances the literature in all three areas. Because productivity growth and agricultural transformation are cornerstone development strategies in SSA, these results are of high value to development stakeholders.

In the third essay, the Nigerian experience with conflicts is used to study their short- and long-term effects on individuals' type of work (namely, family farm enterprises, family non-farm enterprises, and employment with others), and their effects on sectoral employment choices (namely, employment in agriculture, manufacturing, or services). For this purpose, the Nigerian General Household Survey is spatially joined with data on the location of conflict events and their associated number of fatalities. The findings provide evidence of significant labor reallocation effects of conflicts, which arise from the abandonment of farm activities and their replacement by employment in non-agricultural sectors. These effects are observed in both planting and harvesting seasons, suggesting that disruptions occur in both input- and output-related supply chains. Additionally, they differ across gender and skill levels. Hence, in addition to addressing the root causes of conflicts, improving access to education and labor market may be key ingredients of resilience building strategies.

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LIST OF ABBREVIATIONS

ACLED	Armed Conflict Location and Event Data
AEC	Allocative Efficiency Change
AfDB	African Development Bank
AGA	Advice to Avoid Gatherings
AGRA	Alliance for a Green Revolution in Africa
CFL	Curfews and Lockdowns
COVID-19	Coronavirus disease 2019
CRED	Centre for Research on the Epidemiology of Disasters
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DFID	Department for International Development
EM-DAT	Emergency Events Database
ERS-USDA	United States Department of Agriculture Economic Research Service
ETR	Restriction of international travels
FAO	Food and Agriculture Organization of the United Nations
FCT	Federal Capital Territory
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
GFP	Growth of partial factor productivity
GHS	General Household Survey
GMM	Generalized method of moments
GPF	Growth of partial factor productivity
GTFP	Growth of the total factor productivity

HIC	High-income countries
IISS	International Institute for Strategic Studies
ILO	International Labor Organization
IPCC	Intergovernmental Panel on Climate Change
IPW	Inverse Probability Weighting
ISC	Establishment of isolation centers
ITR	Restriction of travels within the country or the area
LGA	Local Government Area
LIC	Low-Income Countries
LP	Linear programming
LRP	Long-Run Propensity
LSMS-ISA	Living Standards Measurement Study - Integrated Surveys on Agriculture
NBS	National Bureau of Statistics
NCDC	Nigeria Centre for Disease Control
NCW	Normal Cumulated Welfare
NEBC	Non-essential businesses closure
NEPAD	New Partnership for Africa's Development
NGO	Non-governmental organization
NLPS	National Longitudinal Phone Survey
NPHCDA	National Primary Health Care Development Agency
OLS	Ordinary Least Squares
PDI	Disinfection of public places
PF	Partial productivity measures
R&D	Research and Development

RCW	Realized cumulative welfare
SAH	Stay-at-home advice
SC	Scale change
SCC	Closure of schools and universities
SE	Scale efficiency
SEN	Sensibilization
SSA	Sub-Saharan Africa
SYS-GMM	System generalized method of moments
TANGO	Technical Assistance to Non-Governmental Organizations
TC	Technical Change
TE	Technical Efficiency
TEC	Technical efficiency change
TFP	Total Factor Productivity
UCL	Université Catholique de Louvain
UN	United Nations
UNDRR	United Nations Office for Disaster Risk Reduction
USAID	United States Agency for International Development
VRS	Variable return to scale
WDI	World Development Indicators
WFP	World Food Program
WHO	World Health Organization
WMO	World Meteorological Organization

CHAPTER 1. INTRODUCTION

1.1. Background

A significant body of literature supports the notion that the growth of the agricultural sector is a key driver of economic development in developing countries (Barrett et al., 2010; Johnston & Mellor, 1961; Lewis, 1954; Ranis & Fei, 1961; Staatz, 1994; Timmer, 1988). Development stakeholders therefore stress the importance of investing in agricultural and rural areas as a means of achieving Sustainable Development Goals (e.g., FAO, 2017; World Bank, 2007). Indeed, in sub-Saharan Africa (SSA), the region of interest in this dissertation, and in developing countries in general, agriculture is the main source of livelihood for most poor people (World Bank, 2007). The preponderance of this region's poverty and food insecurity is frequently associated with low productivity levels, slow technical progress, labor-intensive and family labor reliant agricultural production, weakly resilient production systems, and the dominance of low value-added activities (FAO, 2017b; World Bank, 2007). Consequently, national and regional development agendas tend to emphasize agricultural development (e.g., NEPAD, 2003).

SSA achieved notable macroeconomic progress in recent years. For example, since the year 2000, the agricultural sector grew at a rate of 4.4 percent per year. The industrial and the services sectors grew at rates of 3.1 and 5.1 percent per year, respectively, while the overall economy grew at 4.3 percent per year[1]. To assess these performances in relative terms, note that the agricultural growth rates recorded in all low-income countries (LIC) and in the world in general were 2.5 and 2.8 percent per year, respectively. Productivity gains were also observed during this period in SSA. In constant 2015 US $ terms, the agricultural value-added per worker increased at

[1] The figures reported in this section are all retrieved from the World Bank's World Development Indicators. Otherwise, the source is mentioned. The annual growth rates reported in this section correspond to the mean growth rate over the period 2000 to 2019, which was computed using the exponential growth rate formula.

a rate of 3 percent per year, from 869 in 2000 to 1,526 in 2019. The latter figure is lower than the world average (4,035), but more than 80 percent higher than the LIC's average (824)[2]. While agricultural growth is essential, economic transformation is another important phenomenon. It means the process by which the gains in agriculture are transferred to other sectors of the economy (Barrett et al., 2010; Johnston & Mellor, 1961; Lewis, 1954; Ranis & Fei, 1961). While the growth numbers in SSA are impressive, the NEPAD (2003) stresses that they were not high enough to transform the economy.

Indeed, despite the gains in productivity and value-added recorded, the paces of agricultural and economic transformation are considered slow and incapable of creating enough decent jobs (NEPAD, 2003). While the agricultural sector contributed only 2.8 percent of the GDP in high-income countries (HIC) in 2019, it contributed 16.4 percent of the GDP in SSA. This indicates how far the degree of economic transformation in SSA is from those achieved in developed countries. In addition, it is estimated that the 16.4 percent of GDP was generated by 52.9 percent of the regional workforce, which reflects low income per worker in this sector. The share contributed by industry to GDP decreased at a rate of 0.3 percent per year during the period 2000-2019, reaching 27.1 percent in 2019, compared to 32.9 and 22.6 percent per year in middle and high-income countries, respectively. The services sector contributed 49.9 percent of the GDP and 36.4 of the total employment in 2019. However, this is dominated by the informal sector (NEPAD, 2003). The latter also accounts for 70 percent of the employment in SSA (NEPAD, 2003).

[2] While the figures presented in this section provide an overview of the economic performances at a regional scale, it is worth noting that they mask important country-level heterogeneity of these performances.

Consequently, poverty and food insecurity remain alarmingly high. For example, in 2018, 40.4 percent of the population in SSA was living on less than $1.90 a day (at 2011 international prices), and 22.9 percent of the population lived in households classified as severely food insecure. Given the high dependence of the majority of the poor on natural resources, low productivity and high levels of poverty are major drivers of land degradation and ultimately limit the sustainability of the farming systems (ECA, 2007; ELD Initiative & UNEP, 2015; Le et al., 2016; Nkonya et al., 2016). Le et al. (2016) estimated that 12% of cultivated land in Sub-Saharan Africa is degraded and 22% of the region's population lives in degraded areas (Le et al., 2016).

1.2. Nature and importance of shocks and stressors

Shocks and stressors refer to various events that threaten human life and livelihoods, whether anticipated or unanticipated (Béné et al., 2016). Depending on the duration of exposure to the event, one may distinguish between rapid shocks that are short and unpredictable, medium-term stressors that last several months or frequently occur, and long-term trends that occur gradually over a long run (Béné et al., 2016). Based on their nature or origin, these events can also be classified as either natural disasters, conflicts, or economic shocks.

Natural disasters include floods, storms, earthquakes, extreme temperatures, landslides, droughts, wildfires, volcanic activities, mass movements, epidemics, and infestations. Some of these events are purely natural events (i.e., events that occur naturally independently of human activities, e.g., earthquake or volcanic activity) while others are mixed-cause events (i.e., events that are natural but whose effects and/or frequency are exacerbated by human activities, or vice-versa, e.g., floods and epidemics). Between the period 1980-99 and the period 2000-19, the total number of disasters in the world increased from 4,212 to 7,348 (CRED & UNDRR, 2020). Increases occurred in all main categories. Specifically, the number of flood incidents rose from

1,389 to 3,254, droughts from 263 to 338, earthquakes from 445 to 552, extreme temperatures from 130 to 432, landslides from 254 to 376, storms from 1,457 to 2,043, volcanic activities from 84 to 102, and wildfires from 163 to 238. Only the number of mass movements events decreased, from 27 to 13 (CRED & UNDRR, 2020). The number of people affected by these disasters increased from 3.25 to 4.03 billion people, the number of deaths from 1.19 to 1.23 million people, and the economic losses increased from US$ 1.63 to US$ 2.97 (CRED & UNDRR, 2020). Droughts in East Africa in 1975 (Ethiopia and Somalia) and in 1983-84 (Mozambique, Ethiopia, and Sudan) caused more than 600,000 deaths; storm Katrina caused US$ 146.89 billion in economic losses in the United States; extreme temperatures in China caused US$ 22.49 economic losses in 2008 (WMO & UCL, 2014).

The ongoing COVID-19 pandemic exacerbated the problems from the growing incidence of conflict and other shocks. It has had a huge death toll to date and is associated with mounting socioeconomic costs. According to the WHO Coronavirus Dashboard, as of April 1, 2022, the COVID-19 pandemic had caused more than 6 million deaths worldwide (WHO, 2022). The pandemic and the emergency policy responses led to a dual health-policy shock that caused a global recession in 2020 and pushed an estimated 114.4 million people into extreme poverty (UN, 2020, 2021, 2022). Several international institutions have stressed the alarming impacts of the pandemic and how it undermines the progress towards sustainable development (AfDB, 2021; FAO, 2021b; World Bank, 2021a; Zeufack et al., 2021). Climate change is a long-term trend that is expected to aggravate extreme weather events, thus threatening health, livelihoods, food security, water supply, human security, and economic growth (IPCC, 2018). For instance, it is associated with more inequalities and a slower rate of growth per capita accumulation in Africa (Baarsch et al., 2020).

In contrast to natural disasters, economic shocks and conflicts are man-made events, i.e., events that occur solely as a result of human activities. These events also pose serious human welfare challenges. Major economic shocks in history include the Great Depression (1929-39), the Oil Price Shock (1973), the Financial Crisis (2007-08), and the World Food Price crisis (2007-08). For example, the spike in food prices between January 2007 and January 2008 is estimated to have increased poverty by between 130 and 155 million people (World Bank, 2009). On the other hand, conflicts have also threatened human welfare in many countries. A conflict may be defined as the use or threat of physical force by groups. The types of conflicts include state actions against other states or against civilians, civil wars, electoral violence between opposing sides, communal conflicts based on regional, ethnic, religious or other group identities or competing economic interests, gang-based violence and organized crime and international nonstate armed movements with ideological aims" (World Bank, 2011). While 43 countries recorded lower levels of terrorist activity from 2008 to 2020, 97 recorded higher levels (Institute for Economics & Peace, 2020). Since 2011, the number of conflicts and the number of countries that have experienced conflicts have been increasing (Palik et al., 2020). In addition, the number of state-based conflicts[3] recorded in 2019 (54) is a record high since 1946 (Palik et al., 2020). Conflicts also lead to the displacement of civilian populations, destruction of national infrastructure, and disruption of the political order (IISS, 2018). It was estimated that the global adverse economic impact of violence was $14.5 trillion PPP in 2019, equivalent to 10.6 percent of global GDP or $1,909 per person (Institute for Economics & Peace, 220). Hence, the evidence is strong that shocks and stressors reduce various

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[3] A state-based conflict is defined by as "a contested incompatibility over government and/or territory, where at least one party is a state, and the use of armed force results in at least 25 battle-related deaths within a calendar year" (Palik et al., 2020).

forms of economic activities. However, whether they affect economic transformation needs to be investigated.

In light of the above, a major concern of policymakers is the projected rise in the frequency of some shocks in the near future. For instance, the probability of experiencing a pandemic similar to COVID-19 in one's lifetime is about 38%, and this probability is expected to double in the coming decades (Marani et al., 2021). Hence, as these shocks and stressors are increasingly retarding growth and development, preventing them or mitigating their effects must be part of the development agenda of developing countries. Development stakeholders are therefore now prioritizing resilience building at individual, household, and community levels (FAO, 2021a; Jayne et al., 2021; World Bank, 2013a).

1.3. Resilience, Vulnerability, and Fragility

The concept of resilience is not new. Indeed, economists inherited years of study on how physical or ecological systems resist various forms of disturbance (see Gunderson, 2000; Holling, 1973). In his seminal paper, Holling (1973) defined resilience as the property that "determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist". The heuristic of the ball in cup illustrated in Figure 1 provides an intuitive description of this concept. As Gunderson (2000) summarizes, the ball represents the system's state, each valley is a stability domain, and the system's stability or equilibrium is achieved when the ball lies at the bottom of a cup. A disturbance shakes the cup. As a result, the ball may (a) temporarily move and return to its initial position within the same valley, (b) move to another valley if there are several valleys, or (c) be ejected from the cup. Resilience in engineering refers to the characteristics of the shape of the cup which determines the return time of the ball to the bottom of the cup (e.g., the slopes of the valleys or the sides of the cup) (Gunderson, 2000). In ecology, resilience refers to the width at the top of the cup (Gunderson, 2000). It captures the limits or width of the stability domains in the sense that once the system crosses these limits, its state changes (Gunderson, 2000; Holling, 1996).

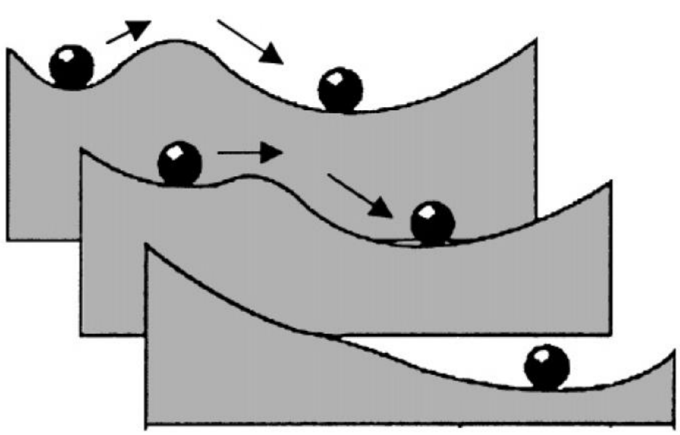

Figure 1: Schematization of the resilience using the ball in cup heuristic
Source: (Gunderson, 2000)

Ecological or engineering systems are characterized by one or several stability domains or stable equilibria, and a shock may cause the system to move to another stability domain. Similarly, in development economics, the literature on welfare dynamics, conditional convergence, and poverty traps suggests that the welfare trajectory is also characterized by multiple equilibria or basins of attraction (equivalent to the stability domains discussed above) which are normatively ranked. That is, a better equilibrium reflects a more desirable socioeconomic status (Arunachalam & Shenoy, 2017; Azariadis & Stachurski, 2005; Barrett & Carter, 2013; Carter & Barrett, 2006). The concept of resilience in development economics was then developed to capture the ability of a socioeconomic unit (e.g., individual, household, community, nation, etc.) to withstand the effects of shocks that tend to push them toward less desirable equilibria. By withstanding these shocks, the socioeconomic unit is able not only to return to its initial equilibrium following a shock, i.e., to bounce back, but also pursue its longer-term progress toward a more desirable equilibrium. For instance, at the macroeconomic level, although an economic shock may cause a sudden drop in the Gross Domestic Product (GDP) per capita, countries are able to return to return to their pre-shock levels (bounce back) and maintain the long-term growth in GDP per capita.

The figure below illustrates these processes by showing the evolution of GDP per capita in the world and in the Sub-Saharan Africa (SSA) region. The financial crisis of 2007-2008 caused GDP per capita to fall globally, but to slowdown in SSA. Subsequently, economies were able to bounce back to the pre-crisis levels from 2009 to 2010. It can also be observed that the long-term positive trend in the GDP per capita is maintained. Similarly, the outbreak of the COVID-19 pandemic also caused a global decline in the GDP per capita from 2019 to 2020. Thereafter, economies gradually recover their pre-pandemic levels of GDP per capita starting from 2021.

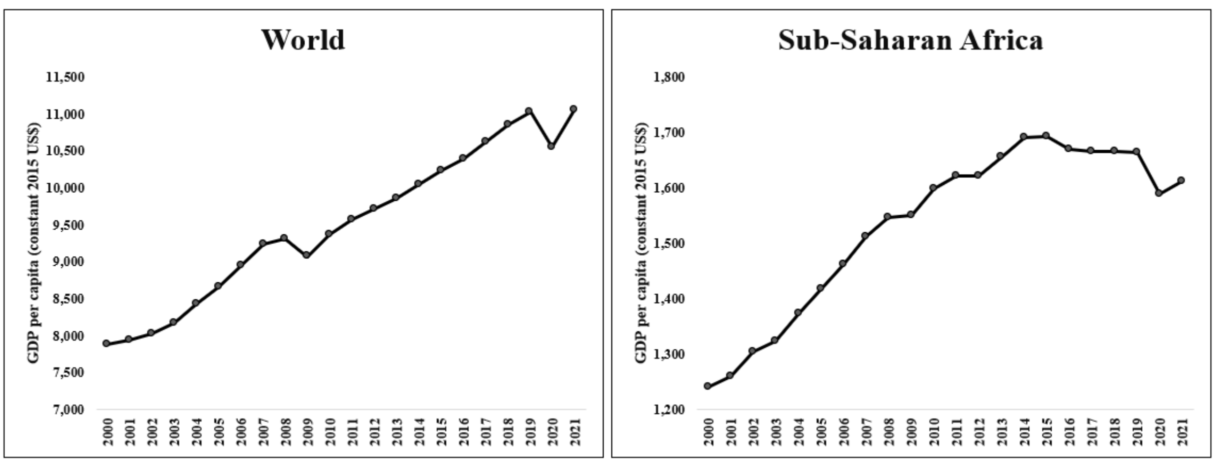

Figure 2: Evolution of GDP per capita in the world and in the Sub-Saharan African region
Source: World Bank World Development Indicators

Preventing individuals or households from falling into poverty as a result of a shock is a major concern of development stakeholders (see, for instance, AfDB, 2021; Atanda & Cojocaru, 2021; Bowen et al., 2020; Ouadika, 2020). In this vein, Barrett & Constas (2014) defined development resilience as "the capacity over time of a person, household or other aggregate unit to avoid poverty in the face of various stressors and in the wake of myriad shocks". Another definition of resilience is "the ability of people, households, communities, countries, and systems to mitigate, adapt to, and recover from shocks and stresses in a manner that reduces chronic vulnerability and facilitates inclusive growth" (USAID, 2012). The USAID definition highlights three main processes underlying the resilience capacity: mitigation, adaptation, and recovery. Furthermore, both definitions consider the specificities of socioeconomic units that differentiate them from the units studied in ecology or engineering. As Barrett & Constas (2014) pointed out, key specificities include their ability of exercising agency, aspiring for better, and the fact that the condition of each individual is as important as that of the population.

Vulnerability and fragility are also important concepts. Vulnerability can be defined as the exposure of an economic unit to exogenous shocks or the degree to which its well-being is affected by the occurrence of the shock (Briguglio et al., 2009; Flatø et al., 2017). It includes the predisposition to be adversely affected, the sensitivity or susceptibility to harm, and the lack of capacity to cope and adapt (IPCC, 2014b). The terms "*fragility*" or "*fragile state*" may be defined as "a fundamental failure of the state to perform functions necessary to meet citizens basic needs and expectations" (Mcloughlin & Idris, 2016) or states where "the government cannot or will not deliver core functions to most of its people, including the poor" (DFID, 2005). High degrees of fragility or vulnerability and weak resilience positively correlate with socioeconomic and institutional conditions that hinder economic development. For instance, they are frequently associated with poor governance, political instability, insecurity and conflicts, corruption, extreme poverty, and food insecurity (Carvalho, 2006; DFID, 2005; Mcloughlin & Idris, 2016).

1.4. Objectives of the dissertation

The overarching objective of this dissertation is to fill some gaps in the literature on the nexus between shocks, resilience, and economic development in the sub-Saharan African context. For such purpose, it mixes micro and macro scales studies to understand how some of the most frequent shocks occurring in this region disrupt the processes of agricultural and economic transformation. In addition, it intends to identify the factors that determine the resilience of economic units in the presence of the shocks investigated.

1.5. Components of the dissertation

The first essay investigates the COVID-19 context, the most recent form of shock at the global scale. This pandemic induced various policy responses, which amount to policy shocks for households. Although research has been done on the economic impacts of the pandemic, this essay intends to contribute to the literature by estimating the individual impact of six policy responses, showing which resilience factors matter in this context, and deriving the implications for the resilience-building process. This investigation is important because oftentimes, the role of policies is ignored. In addition, farmers have diminished political voice in many countries, so it is easy to implement policies without thinking about the impact of these policies on agriculture. The outcome variables considered are farm and non-farm incomes, where non-farm incomes include the incomes from non-farm family businesses and wage employment.

The second essay is a macro-level investigation of the impacts of conflicts and droughts on productivity. It is based on a productivity approach because of the fundamental importance of the productivity concept in agricultural and economic development. While most early works on development focus on productivity, few addressed the impact of shocks on productivity growth, especially from a long-run perspective. In essay 2, the outcome variables are the measures of partial factor productivity and total factor productivity (TFP). It presents technical frameworks for decomposing growth into the growth of inputs and TFP, linking TFP to partial factor productivities, and decomposing TFP into various types of efficiencies. The subsequent estimation of the impact of selected shocks on productivity and efficiency measures enables one to trace the effect of a particular shock on growth dynamics through the efficiency of use of each input. In addition, linking productivity measures to shocks using a distributed lag model enables one to provide an alternative measure of resilience. Hence this essay also contributes to the methodology for explaining and analyzing resilience.

The third essay examines the impact of conflict on the allocation of the labor to different types of activities (namely family farm and nonfarm activities, and employment outside the household) and on sectoral employment choices (namely, employment in agriculture, manufacturing, or services). The focus on the labor reallocation effects of conflict is justified first by the fact that the reallocation of labor is one of the most popular coping strategies used by individuals and households facing various types of shocks and stressors especially in developing countries. Second, labor reallocations directly affect the livelihood diversification at the individual or household levels, which is a key component of the resilience capacity. Third, labor reallocations can have a direct impact on sectoral productivities, which in turn determine the trajectory of economic transformation. In addition, this essay analyzes how these effects differ between women and men and between low- and high-skilled workers. It also examines how the effects differ between the planting and the harvesting seasons in order to proxy the effects on planting and harvesting related supply chains. Taking these sources of heterogeneity into account allows to derive more specific policy implications on how to better protect incomes in conflict-prone areas.

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CHAPTER 2. ESSAY 1: ENDOGENOUS POLICY RESPONSES TO COVID-19, RESILIENCE FACTORS, AND THE IMPACT OF THE PANDEMIC ON FARM PERFORMANCE

2.1. Introduction

Concerns about the eruption of the COVID-19 pandemic and the massive loss of human life associated with it triggered a wave of emergency policy responses across the world, with differing levels of stringency. While these policy responses induced by the outbreak were mainly aimed at protecting human health, they also had direct economic impacts on individuals and households and may have threatened livelihoods.

Despite the considerable research interest on the adverse effects of these policy responses on households' welfare, several gaps persist. First, while several papers identified households' socio-economic outcomes affected by the policy responses or how they affected the households' economic environment (e.g., Adjognon et al., 2021; Ahmed et al., 2021; Amare et al., 2021), few papers (e.g., Amare et al. 2021) paid attention to the effect of policies issued at subnational levels. Second, these studies either only consider the policy regarded as the most stringent or just estimate the effect of the period of containment measures, thus lumping all measures together. Nevertheless, a comprehensive analysis must consider all the steps taken by central and local authorities and treat them separately. In addition, there is no consideration of households' awareness of the issuance of these policies, which is important given the heterogeneous access to information in developing countries and the dependence of households' behavioral responses on their awareness.

Third, while studies identified the factors explaining how the harmful effects of the pandemic vary across the population, they provide a poor understanding of the differential impact between farm and nonfarm households. Although Amare et al (2021) found that farm households suffered from a rise in food insecurity during the pandemic, additional research is needed to explain why. Because agricultural households are both consumers and producers, and both labor suppliers and demanders, there may be potential benefits for agricultural households in addition to adverse effects. Therefore, the net economic effect of the pandemic on this group of households is hardly predictable. Furthermore, little is known about the heterogeneity of the pandemic's impact among farmers based on farmers' characteristics. Last, previous studies also pinpointed that households responded to these endogenous policy shocks mainly through consumption smoothing. However, the households' responses are only one component of their overall ability to withstand the health and policy shocks, called resilience. The latter also includes the ability of the household to take advantage of the changing environment induced by the shock to gain short- and long-term benefits. Thus, a more comprehensive analysis must consider every component of households' resilience.

This essay addresses these gaps by first providing a theoretical model that explains the pathways through which the pandemic affects agricultural households' income. Household-level data from two surveys implemented in Nigeria are then used to estimate the individual impact of six policy responses issued either by the federal or state governments on the income of these households. Using income as an indicator of farm households' welfare is appropriate since it is correlated with their poverty and food security levels. In addition, the change in farm income is an indicator of farm viability, a critical development outcome. Moreover, I examine under which conditions Nigerian agricultural households were able to absorb the policy shocks, which parameters allowed them to adjust and take advantage of the changing economic conditions, and which policies were transformational for them.

Nigeria is an optimal choice for the empirical analysis. Indeed, Nigeria has the largest population in Africa. The economic challenges faced by Nigeria are similar to those faced by most countries in the region. For instance, Nigerian public finances are highly dependent on oil prices, 40% of the population lives below the poverty line, and an additional 25% is considered vulnerable (World Bank, 2021b). On top of that, the subnational disparities in terms of economic opportunities and enabling social, environmental, institutional, and infrastructural environment that Nigerian households experience are representative of the conditions existing in the majority of sub-Saharan African countries and even in many non-African developing countries. An additional dimension of the Nigerian representativeness is the rising frequency of and cumulating experience with several types of shocks and stressors, including armed conflicts (e.g., Boko Haram insurgencies), natural disasters, medium- and long-term stressors (e.g., floods and desertification), and epidemics (e.g., Ebola and COVID-19). Nigeria was the first country to confirm a case of COVID-19 in sub-Saharan Africa. The size of the country and its population and the inter-state differences in vulnerability to this type of shock cause a rising but heterogeneous incidence of the pandemic. The relatively more decentralized health governance system introduces a subnational variability in the COVID-19 policy responses, contributing to these trends (Oleribe et al., 2019). The Nigerian health system also faces similar challenges as its regional counterparts, including the lack of sufficient financial resources, the lack or inappropriateness of human resources, deficiencies in healthcare infrastructures and their maintenance, issues in management and leadership, among others (Oleribe et al., 2019).

This essay contributes to the literature by identifying which containment measures harmed farmers, which ones did not, and which ones were beneficial for farmers while specifying which type of farmers were more affected. It also highlights the role of resilience capacities in the context of the COVID-19 pandemic. Finally, to obtain a more comprehensive picture of the impacts on farmers' welfare, I examine their effects on non-farm sources of income, namely the non-farm family businesses and wage employments. For all these reasons, the findings are of high value for the improvement of policy responses in the context of the ongoing pandemic. Moreover, since the occurrence of health shocks similar to COVID-19 are highly likely in the coming decades (Marani et al., 2021), this study is also relevant for policy responses to upcoming health shocks because such policies will be expected to protect health while minimizing their adverse economic effects.

The remainder of this study is organized as follows. Section 2.2 provides the Nigerian context and experience with the pandemic and explains the different pathways through which the pandemic may affect agricultural households, and by extension, actors along the food and inputs supply chains. It also presents the development resilience theory upon which this essay is grounded. It further theoretically links COVID-19, resilience, and farm income. Section 2.3 models the effect of the pandemic and the associated policy responses based on an agricultural household model. Section 2.4 presents the data and the empirical strategy. Section 2.5 presents the findings of this research. The essay concludes with section 2.6, which provides a summary, conclusions, and policy recommendations.

2.2. Background

In this section, through a literature review, I provide backgrounds on Nigeria, its COVID-19 experience, the impact on agriculture, and the nature and role of resilience factors.

2.2.1. The Nigerian experience with COVID-19

Six years after the 2014 Ebola epidemic, the Nigerian health system was again put to the test by the COVID-19 pandemic. On February 27, 2020, Nigeria's Federal Ministry of Health confirmed the first case of COVID-19 in sub-Saharan Africa. One year later, by January 31, 2021, the number of confirmed cases in the country had reached 131,242, while the number of deaths reached 1,586 (NCDC, 2021b). The numbers have continued to increase since then, reaching 210,460 confirmed cases and 2,882 deaths by October 24, 2021 (NCDC, 2021a). The Federal

Capital Territory (FCT), the states of Kaduna, Lagos, and Rivers are the most affected, while the state of Kogi is the least affected. Most of the states along the northern border have fewer cases (see Figure 3) (NCDC 2021b).

The federal and state governments responded through temporary measures, including stay-at-home orders, curfews, closures of schools and workplaces, bans on social gatherings, cancellation of public events, land borders closure, restrictions of international travels and travels in the country (Dan-Nwafor et al., 2020; Nachega et al., 2021; Nhemachena & Murwisi, 2020). Internet, social media, SMS, and radio were also mobilized to combat misinformation and transmit information on the location of testing and isolation centers (Nachega et al., 2021). The rollout of the COVID-19 vaccine began in March of 2021, and the Federal Government aims to have enough vaccines for 70% of the population by 2022 (Usigbe, 2021). However, distrust of the vaccine and hesitancy to be vaccinated remain major challenges for authorities, along with many financial and technological challenges (Nachega et al., 2021; Usigbe, 2021; WHO, 2021). As of October 28, 2021, only 5.1% of the eligible population had received their first dose, while only 2.7% had received their second dose (NPHCDA, 2021).

Figure 3: Distribution of cumulative cases of COVID-19 in Nigeria on October 24, 2021
Source: (NCDC, 2021a)

The containment measures and the decline in oil prices led to a recession in 2020 mainly driven by the negative growth rates in industry and services (World Bank, 2021b; Zeufack et al., 2021). However, the undertaking of monetary and fiscal reforms and the recovery of oil prices enabled the economy to start bouncing back in 2021 (World Bank, 2021b; Zeufack et al., 2021). The agricultural sector did not experience a negative growth rate during the 2020 recession, but its growth rate decreased compared to the pre-recession period (Zeufack et al., 2021). The next sub-section explains the pathways through which the pandemic may affect the farm sector.

2.2.2. Covid's impacts on agriculture

Farmers suffered from the vulnerability of the entire food value chains to the pandemic (Nhemachena & Murwisi, 2020; Reardon & Vos, 2021). They faced labor shortages resulting from reduced productive health (Willy et al., 2020) and labor mobility restrictions (FAO, 2020; Swinnen et al., 2021; Willy et al., 2020). The pandemic disrupted inputs' production and transportation at the global level, which limited the quantity and quality of inputs available to farmers, raised their prices, and exacerbated delivery delays (FAO, 2020; Nhemachena & Murwisi, 2020; Willy et al., 2020).

Transport and logistics of farm inputs and outputs were affected by labor shortages, cross-border movements restrictions, delays in border clearance, and higher frequency of road hassles (AfDB, 2020; FAO, 2020; WFP, 2020; Willy et al., 2020). In addition, some seeds producers found it more difficult to source breeder and foundation seed from neighboring countries (Willy et al., 2020). The reduced availability of quality seeds in the markets led to more marketing of substandard seeds (AfDB, 2020). Besides, the pandemic also lessened farmers' demand for inputs by reducing their earnings, rising food prices, and increasing input prices (Nhemachena & Murwisi, 2020; Willy et al., 2020).

The induced economic shock worsened fiscal challenges. As a result, some governments reduced public expenditures on agriculture which disrupted extension services (FAO, 2020; Willy et al., 2020). Herders suffered from the disruption of veterinary services and vaccination campaigns stemming from movement restrictions and limited access to grazing and watering points (FAO, 2020).

Farmers also endured the disruptions of food demand and markets. Traditional, peri-urban, and urban markets were disrupted by their closure, movements restrictions, and panic buying (FAO, 2020; WFP, 2020), which led to food shortages and price rises, especially in traditional markets. In addition, the exports restrictions imposed by some countries and other forms of disruption of international markets might reduce exports revenues and trigger spikes in food prices in importing countries (Swinnen et al., 2021; Willy et al., 2020). Finally, because the pandemic led to a decline in working hours and employment, job losses, and a drop in remittances, it ultimately reduced consumers' earnings and purchasing power (FAO, 2020; ILO, 2020; Nhemachena & Murwisi, 2020; Swinnen et al., 2021; Willy et al., 2020).

The evidence on the effects of the pandemic on agriculture in Nigeria indicates that the food and inputs supply chains were impacted by the disruption of seed multiplication and certification, disruptions in the hospitality sector, closure of markets, border closures, longer delays at ports of entry, labor shortages, food shortages, rise in food prices, difficult access to food supplies and reduced market demand stemming from income losses (Nhemachena & Murwisi, 2020). One government's response was the recourse to the Strategic Grain Reserves. Nhemachena and Murwisi (2020) reported that the government released 70,000 tons of grain from the National Strategic Grain Reserve for distribution to the poor.

2.2.3. Nature and importance of the resilience approach

The rising frequency of shocks that threaten individuals' and communities' livelihood is a mounting matter of concern. 4,212 disasters were reported during the decade 1980-1999, and this number rose to 7,348 in the decade 2000-2019, along with rising numbers of people affected, deaths, and economic losses (CRED & UNDRR, 2020). Similarly, the number of conflicts is soaring, along with their disastrous consequences (ACLED, 2021; IISS, 2018; Institute for Economics & Peace, 2020; Palik et al., 2020). As a result, development stakeholders are giving priority to building socio-economic resilience (AfDB, 2013; AGRA, 2021; FAO, 2019; Zeufack et al., 2021).

Resilience has quickly gained interest in the development literature and has been defined in various ways (Barrett & Constas, 2014; Cissé & Barrett, 2018; Constas et al., 2014; FAO, 2016; Smith et al., 2015; USAID, 2012; World Bank, 2013b). One notable definition is “the ability of people, households, communities, countries, and systems to mitigate, adapt to, and recover from shocks and stresses in a manner that reduces chronic vulnerability and facilitates inclusive growth" (USAID, 2012). There are also working or applied definitions of resilience, which depend on the shock investigated, the economic unit considered (individual, household, or community), and the development outcomes of interest. The shocks or stressors may either be natural events (i.e., occurring independently of human activities, e.g., earthquake or volcanic activity), man-made events (i.e., occurring solely as a result of human activities, e.g., economic crisis and armed conflicts), or mixed-cause events (events that are natural but whose effects or frequency are exacerbated by human activities, and vice-versa, e.g., floods, desertification, climate change, and epidemics). Applications include resilience to natural disasters (Arouri et al., 2015; Cutter et al., 2008; Lwin et al., 2020), land degradation and droughts (Smith et al., 2015), and conflicts (Aall & Crocker, 2019; Adelaja et al., 2020; Breisinger et al., 2014; van Metre & Calder, 2016). The outcomes considered include well-being indicators such as poverty, food security, and land expansion (Adelaja et al., 2020; Arouri et al., 2015; Smith et al., 2015).

The conceptual view of resilience varies among researchers or organizations (FAO, 2016; Smith et al., 2015; TANGO International, 2018). In this study, I borrow TANGO's conceptual view in which resilience is composed of three capacities (absorptive capacity, adaptive capacity, and transformative capacity) that are interconnected and mutually reinforcing.

The resilience capacities reflect the interplay between individuals, households, and communities' agency on one side and the characteristics of their social, economic, institutional, environmental, and infrastructural environment on the other side. To sum up the descriptions of IPCC (2014a), Smith et al. (2015), Castillo, Jeans and Thomas (2016), FAO (2016) and TANGO International (2018), I define the absorptive capacity as the ability to minimize exposure to shocks and stresses, to take protective actions or preventive measures, to cope with the adverse effects, and to recover from a disturbance. Adaptive capacity is the ability to identify and take advantage of alternative livelihood strategies stemming from the changing environment. Transformative capacity represents the extent to which the institutional, social, economic, environmental, and infrastructural environment of the agent or group of agents enables them to make the fundamental changes that address the structural or root causes of their hardship. It also embodies the extent to which individuals and communities' agency lead them to engage in processes that modify this multidimensional environment whenever the latter appears to be a source of hardship.

While borrowing TANGO's conceptual view of resilience, I do not use their resilience measurement approach based on factor analysis. Instead, I use individual variables as indicators of resilience capacities.

2.2.4. Covid resilience and agricultural income

As section 2.2.2 indicates, the pandemic may affect farmers through several pathways. However, the resilience capacities may enable farmers to modulate the adverse effects of the pandemic and even reap the crisis's short- and long-term benefits. A higher absorptive capacity allows them to minimize the immediate impact of the virus so that they are either not impacted, weakly impacted, or quickly recover from some health or economic damage. For instance, taking the vaccine provides farmers with absorptive capacity so that there is a lower probability that they had to reduce their labor supply after some exposure to the disease.

Depending on their socio-economic characteristics (e.g., level of education, degree of access to market information), some farmers may identify profitable trends in the food demand resulting from the containment measures like higher demand for packaged and delivered foods.

Adaptive capacity means the ability to detect these income-maximizing alternative opportunities and the flexibility of their production system to adjust and seize these opportunities.

Finally, the responsiveness of the government may be transformational. For example, a lockdown may be transformational for farmers who can make the investments required to seize the opportunities induced by this policy. Indeed, these investments mean a rise in the amount of capital, which remains after the crisis and determines their income over the long run. In other words, since the lack of capital is a root cause of poverty, this policy can be transformational for some farmers by creating the opportunity to raise capital. This effect depends on the quality of the economic and institutional environments (e.g., financial services and membership to a farmers' organization), among other factors.

2.3. Theoretical framework

This section provides a model that explains how policy responses to the pandemic and the resilience capacities interact with the shock to determine the impact on the agricultural household's income. The model assumes only one policy but may be extended to a vector of policies.

COVID-19 affects agricultural households through three channels. The first is the *health channel*: individuals affected by the disease and those who take care of them are likely to temporarily reduce or even stop their labor supply, hindering their involvement in farm and nonfarm activities. From the household's perspective, this means that the endowment of family labor is shrunk from its pre-pandemic level (L^T) to its pandemic level $(L^T - L^-)$, where L^- represents the amount of family labor that is not able to work due to the disease. L^- is directly affected by the exposure to the disease (s). The exposure to the disease (s) leads the government to adopt the stringent policy (P) to reduce the level of s. Therefore, in addition to its direct effect on L^-, the exposure to the disease (s) also indirectly affects L^- through its effect on P. The amount of family labor that is not able to work due to the disease is then represented as $L^{-}(s, P)$, where $P(s)$. L^{-} is a non-decreasing function of s and a nonincreasing function of P. P may be viewed as an index that increases with the degree of the policy's stringency or just an indicator taking the value 1 whenever the policy is implemented and 0 otherwise. In either case, P is a non-decreasing function of s.

The second channel through which the outbreak affects the agricultural household is the *transaction costs channel*. Indeed, the pandemic results in a rise in the cost of market transactions for those who sell their output or procure their input on the spot market. Simultaneously, it should also increase the transactions costs (Williamson, 1985) of governing formal and informal contracts guaranteeing output sales or input procurement because the economic shock, the prices changes, and the disruptions along the supply chains might have shifted the incentives of many agents. Moreover, the unexpected nature of the shock is a source of potential hold-up problems (Klein, 1996; Klein et al., 1978) for those engaged in formal or informal contracts. I use the term *transaction cost* to encompass all these contracts and noncontract-related costs. Most of these costs are household-specific, farm-specific, crop-specific, and location-specific (Pingali et al., 2005).

Hence, the *transaction costs channel* stipulates that the stringent COVID-19 related policy (P) imposed by the government as a response to the outbreak creates additional frictions in the access to inputs or outputs markets, thereby raising the transaction costs. Since the policy is adopted as a reaction to the outbreak and increases the transaction costs because of its stringent nature, the transaction costs related to inputs and outputs markets are represented in the model by $\tau_x(P)$ and $\tau_a(P)$, respectively, where $P(s)$. Therefore, both τ are non-decreasing functions of P.

The third channel through which the pandemic affects farmers' welfare is the *price channel*. As explained in previous sections, the policy (P) can cause a rise in input prices, an increase or decrease of output prices, a farm labor shortage, and a variation in consumer prices. Thus, agricultural inputs and output prices are represented in the model by $p_x(P)$ and $p_a(P)$ respectively, agricultural wage as $w_a(P)$, non-agricultural wage as $w(P)$, the price of goods and services consumed as $p_m(P)$, where $P(s)$. p_x is a non-decreasing function of P and p_a can be an increasing or decreasing function of P. w_a and w are non-decreasing functions of P, which capture labor shortage in farm and nonfarm sectors, respectively.

Let L^f and L^h be the amount of family and hired labor involved in farm activities, respectively, while L^w represents the amount of family labor involved in nonfarm activities. C is the vector of quantities of goods consumed.

Equations (1) to (5) below describe the optimization problem of the agricultural household. The budget constraint (equation (2)) imposes the constraint that the household cannot consume more than its income which is the sum of farm income (Π) and nonfarm income ($\widetilde{\Pi}$). The farm income depends on the farm production function (F), the amount of inputs used (x), the effective prices of inputs and outputs ($p_x + \tau_x$ and $p_a - \tau_a$, respectively), amounts of labor employed in farm production (L^f and L^h), the agricultural wage (w_a), and household's characteristics (Z) (see equation (3)). The nonfarm income ($\widetilde{\Pi}$) depends on the labor engaged in non-farm activities (L^w), the non-agricultural wage (w), the prices of various nonfarm products or services that the households may produce and sell (included in p_m and p_x), and household's characteristics (Z) (see equation (4)). Finally, equation (5) shows that the amount of family labor allocated to farm and non-farm activities (L^f and L^w, respectively) cannot exceed the amount of family labor not affected by the disease $(L^T - L^-)$.

The agricultural household solves the problem:

$$\max_{L^f, L^h, L^w, x, C} U = U(C; Z) \tag{1}$$

s.t.,

Budget constraint:

$$p_m(P) \cdot C \leq \Pi + \tilde{\Pi} \quad (2)$$

$$\Pi = [p_a(P) - \tau_a(P)] \cdot F(L^f, L^h, x; Z) - [p_x(P) + \tau_x(P)] \cdot x - w_a(P)L^h \quad (3)$$

$$\tilde{\Pi} = \tilde{\Pi}(L^w, w, p_m(P), p_x(P); Z) \quad (4)$$

Family labor constraint:

$$L^f + L^w \leq L^T - L^-(s, P) \quad (5)$$

where $P(s)$. Solving this problem involves setting up the Lagrangian (see equation (6)) and deriving the first-order necessary conditions.

$$\mathcal{L} = U(C; Z) - \lambda_1[p_m(P) \cdot C - \Pi - \tilde{\Pi}] - \lambda_2[L^f + L^w - L^T + L^-(s, P)] \quad (6)$$

The optimal labor supply, input demand, and consumption decisions may be formulated as:

$$\Gamma^* = \Gamma(w_a(P), w(P), p_x(P), p_a(P), p_m(P), L^-(s, P), \tau_a(P), \tau_x(P), Z) \quad (7)$$

where $P(s)$ and,

$$\Gamma \in \{L^f, L^h, L^w, x, C\} \quad (8)$$

Consequently, the optimal farm and nonfarm incomes may be expressed as:

$$\Pi^* = \Pi^*(w_a(P), w(P), p_x(P), p_a(P), p_m(P), L^-(s, P), \tau_a(P), \tau_x(P), Z) \quad (9)$$

$$\tilde{\Pi}^* = \tilde{\Pi}^*(w_a(P), w(P), p_x(P), p_a(P), p_m(P), L^-(s, P), \tau_a(P), \tau_x(P), Z) \quad (10)$$

where $P(s)$. Equations (9) and (10) show that exposure to the pandemic affects the agricultural household's income through the three channels. The effect through $L^-(\cdot)$ is the *health channel*, the effect through $\tau_a(\cdot)$ and $\tau_x(\cdot)$ is the *transaction costs channel*, while the effect through the $w(\cdot)$ and $p(\cdot)$ represents the *prices channel*. The *immediate* impact of a rise of the agricultural household's exposure to the disease on the household's farm income is:

$$\frac{\partial \Pi^*}{\partial s} = \left[\frac{\partial \Pi^*}{\partial L^-}\right]\frac{\partial L^-}{\partial s} + \left[\frac{\partial \Pi^*}{\partial L^-}\frac{\partial L^-}{\partial P} + \sum_{\tau \in \{\tau_a, \tau_x\}} \frac{\partial \Pi^*}{\partial \tau}\frac{\partial \tau}{\partial P} + \sum_{\eta \in \{w_a, w, p_x, p_a, p_m\}} \frac{\partial \Pi^*}{\partial \eta}\frac{\partial \eta}{\partial P}\right]\frac{\partial P}{\partial s} \qquad (11)$$

The effect on the nonfarm income may be derived similarly.

$\frac{\partial \Pi^*}{\partial L^-}$ represents the direct effect of the shrinkage of family labor endowment on farm income and is expected to be negative. Moreover, the value of this fraction depends on the characteristics of the production system, like the degree of labor intensity versus mechanization. A mechanized farm should suffer from this shrinkage more than a farm relying more on the human workforce. Therefore, mechanization provides the household with some absorptive capacity. Depending on its financial resources, a household may also be able to substitute family labor with hired labor, which reflects its adaptive capacity. The more financial capacity or, the higher degree of mechanization, the less the value of $\frac{\partial \Pi^*}{\partial L^-}$. These examples illustrate how the resilience factors enter the model: they determine every single fraction in equation (11). $\frac{\partial L^-}{\partial s}$ is the direct effect of a higher exposure on the degree of shrinkage of family labor endowment and is expected to be positive. It depends on factors like the vaccination status, the household members' compliance with the containment measures, access to information on sanitary advice, all of which provide the household with absorptive capacity.

$\frac{\partial L^-}{\partial P}$ is the direct effect of the policy on the amplitude of family labor reduction and should be negative. Since the policy is used to mitigate the health damage on the population, it offers some absorptive capacity that limits the amplitude of this fraction.

$\frac{\partial \Pi^*}{\partial \tau}$ is expected to be negative and represents the direct effects of a rise in transaction costs on the farm income. A farmer with higher adaptive capacity may limit the value of this fraction by switching to the products for which the transaction costs increased to a weaker extent. This flexibility may be indicated by resilience factors like the degree of access to information, education, and membership in a cooperative. The diversity of income sources also attenuates the effect of the rise of transactions costs associated with some specific products on the farm income, offering some absorptive capacity.

$\frac{\partial \tau}{\partial P}$ should be positive and translates how the policy raises the transaction costs.

$\frac{\partial \Pi^*}{\partial \eta}$ represents the direct impact of the wage or price η on the farm income. If η is an output price, this fraction is positive, but if η is an input or consumption price, this fraction is negative. When it is negative, resilience factors tend to limit its extent but augment it when it is positive. For instance, the adaptive capacity enables the farmers to switch to the supply of a product whose price increased on the market.

$\frac{\partial \eta}{\partial P}$ captures the direct impact of the policy on prices or wages. The positive value of this fraction will capture a labor shortage due to the policy. In contrast, a drop of an output price due, for instance, to an export ban will be captured by a negative value of this fraction.

$\frac{\partial P}{\partial s}$ reflects the reaction of the government to a rise of exposure to the disease. Its expected positive value reflects that higher exposure to the disease leads the government to adopt a stringent policy.

As a result, $\left[\frac{\partial \Pi^*}{\partial L^-}\right] \frac{\partial L^-}{\partial s}$ captures the direct impact of a rise of exposure to the disease on farm income throughout the *health channel*. $\frac{\partial \Pi^*}{\partial L^-} \frac{\partial L^-}{\partial P}$ represents the impact of the policy triggered by the pandemic on farm income throughout the *health channel* and is the indirect impact of the exposure to the disease throughout the *health channel*. $\sum_{\tau \in \{\tau_a, \tau_x\}} \frac{\partial \Pi^*}{\partial \tau} \frac{\partial \tau}{\partial P}$ represents how the policy impacts farm income throughout the *transaction cost channel*. $\sum_{\eta \in \{w_a, w, p_x, p_a, p_m\}} \frac{\partial \Pi^*}{\partial \eta} \frac{\partial \eta}{\partial P}$ captures how the policy affects affect farm income throughout the *prices channel*. All these effects depend on the level of resilience factors.

Consequently, the sign of the effect of higher exposure to the disease on the household's income is unclear, which confirms why agricultural households are different from others. A simplified version of equation (11) that suits more the empirical model is obtained by examining the *immediate* impact of the policy:

$$\frac{\partial \Pi^*}{\partial P} = \frac{\partial \Pi^*}{\partial L^-}\frac{\partial L^-}{\partial P} + \sum_{\tau \in \{\tau_a, \tau_x\}} \frac{\partial \Pi^*}{\partial \tau}\frac{\partial \tau}{\partial P} + \sum_{\eta \in \{w_a, w, p_x, p_a, p_m\}} \frac{\partial \Pi^*}{\partial \eta}\frac{\partial \eta}{\partial P} \tag{12}$$

The net effect of the policy is then the result of the extent to which it protects farmers' income throughout the *health channel* $\left(\frac{\partial \Pi^*}{\partial L^-}\frac{\partial L^-}{\partial P}\right)$, the extent to which it degrades farmers income throughout the *transaction cost channel* $\left(\sum_{\tau \in \{\tau_a, \tau_x\}} \frac{\partial \Pi^*}{\partial \tau}\frac{\partial \tau}{\partial P}\right)$, and its cumulative disruptive impacts on labor and products markets $\left(\sum_{\eta \in \{w_a, w, p_x, p_a, p_m\}} \frac{\partial \Pi^*}{\partial \eta}\frac{\partial \eta}{\partial P}\right)$.

2.4. Empirical framework

2.4.1. Data

The data used result from the combination of two World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) conducted in Nigeria in collaboration with the Nigerian Bureau of Statistics (NBS). The first, named the 2018-2019 General Household Survey (henceforth referred to as GHS), is a face-to-face nationally representative survey carried out before the pandemic and is the fourth and last wave of the Nigeria General Household Survey panel (GHS-P). The previous rounds were collected in 2010-2011, 2012-2013, and 2015-2016. This survey provides me with households' socio-economic characteristics that enter the set of explanatory variables. The second survey I use is the COVID-19 National Longitudinal Phone Survey 2020 (henceforth referred to as NLPS) implemented during the pandemic. The households interviewed in the NLPS were drawn from the households interviewed in the 2018-2019 GHS survey. Each month during the pandemic, they were asked a set of questions related to the COVID-19 restrictions and socio-economic outcomes. For detailed information about both surveys, the reader is referred to NBS and World Bank (2019) and (2020).

As part of the NLPS, the households were asked in August 2020 (round 4 of the NLPS) whether their income from different income sources increased, stayed the same, or decreased compared to August 2019 (before the pandemic). I use this discrete information to create two types of binary dependent variables. The first type takes on the value 1 if the income increased and 0 otherwise, while the second takes on the value 1 if the income decreased and 0 otherwise. Since the factors that induce farmers' income to increase are not exactly the same that make it decrease, investigating a factor's effect on the likelihood that farmers' income increased is not the exact opposite of investigating this impact on whether it decreased.

During the NLPS, the households were also asked which measures the federal or state government took to mitigate the spread of the coronavirus in their area. The measures or policies covered include the stay-at-home advice (henceforth referred to as SAH), the advice to avoid gatherings (henceforth referred to as AGA), the restriction of travels within the country or the area (henceforth referred to as ITR), curfews and lockdowns (henceforth referred to as CFL), closure of non-essential businesses (henceforth referred to as NEBC), and the closure of schools and universities (henceforth referred to as SCC), the restriction of international travels (henceforth referred to as ETR), the sensibilization (henceforth referred to as SEN), the establishment of isolation centers (ISC), and the disinfection of public places (PDI). I do not include ETR, SEN, ISC, and PDI in the analysis because they are complementary measures often adopted along with the main policies and are not expected to affect agriculture directly.

I use households' answers to generate binary variables equal to 1 whenever the policy is issued and 0 otherwise. Asking a household whether the federal or state government took a specific measure in their state or area enables to proxy the household's awareness of the issuance of the policy, which cannot be expected to be the same for every household. Some previous studies used the statements of policies issued at the federal or state levels (e.g., Amare et al. 2021) which represent the policies' issuance by a government but not the awareness of each individual of their issuance. Capturing households' awareness is essential because the behavior of the household as a response to the shock depends on its level of awareness.

Using dependent variables generated from the self-reported sign of income change means the results may suffer from recall bias. In addition, it prevents me from taking advantage of the panel structure of the GHS-P because the question on which the dependent variable is based (i.e., the sign of change in the income from a specific source from August of a specific year to August of the following year) was not asked in all four waves of the GHS-P. Still, given the need to include household level variability in policies to which households are subject and the households' awareness, this is the most accurate data available. In addition, the households have been asked to compare their current income with that from the same month of the previous year, which limits the recall bias because respondents are more able to compare their current situation with their situation in the same season in the precedent year. Moreover, the NLPS has the advantage of providing information on each type of policy measure and disaggregating income change by source of income. The LSMS team also produced a harmonized dataset that combines some information collected from these two surveys to facilitate their joint use. More precise empirical results should be obtained using a continuous measure of income change, but the available data do not enable me to get such a measure.

The pre-pandemic values of households' socio-economic characteristics are generated using the GHS dataset or directly extracted from the harmonized dataset. The variables generated are the proportion of hours worked by hired workers, the share of crops that are processed and sold, the values of the livestock and assets, a binary indicator representing whether a member of the household was a recipient of a safety net, and the Normalized Herfindahl–Hirschman Index of income diversification.

As a result, I obtain a sample of 1,388 agricultural households for which I have data on the sign of farm income change from August 2019 (pre-pandemic) to August 2020 (during the pandemic). I associate each household with its cross-section weight calculated by the LSMS team. These weights enable to get estimates that are representative of the national population using households that were successfully interviewed (NBS & World Bank, 2020). For further details about the computation of these weights, the reader is referred to NBS and World Bank (2020). Moreover, I test whether excluding nonfarm households leads to a sample selection bias using a Heckman Selection Model, and the result is negative because the Inverse Mills Ratio is not statistically significant (see appendix A1, tables 37 and 38). Moreover, the econometric estimations only consider households with no missing values of explanatory variables because I prefer to impose the fewest assumptions on the missing data mechanism.

Table 1 presents the descriptive statistics associated with the sample of agricultural households. 31% of them benefited from an increase in their farm income during the pandemic, while 56% reported that it decreased. Concerning the policy responses' coverage, the majority of the households surveyed (72%) were advised to stay at home. The second most widespread policy was the advice to avoid gathering (66%), followed by curfew or lockdown (45%), closure of schools and universities (35%), restriction of travel within country or area (34%), and the closure of non-essential businesses (32%). The average land size in the sample is 0.85 ha. The proportion of hours worked by hired labor and the share of crops processed and sold vary from 0 to 100% with means of 33% and 3%, respectively. 11% of the households were the recipient of a safety net before the pandemic. The value of the Normalized Herfindahl–Hirschman Index of income diversification (0.75) indicates that most households have few alternative sources of income. The value of the livestock ranged from 0 to 12,564,000 Naira, with a mean of 141,880 Naira. The value of households' assets ranged from 400 to 150,169,500 Naira, with a mean of 409,440.

Table 1: Descriptive statistics

Variable definition	Variable name	Obs	Mean	Std. Dev.	Min	Max
Farm income increased (= 1 if farm income increased, 0 otherwise)	IIF	1,388	0.31	0.46	0	1
Farm income decreased (= 1 if farm income decreased, 0 otherwise)	IDF	1,388	0.56	0.50	0	1
Advised citizens to stay at home	SAH	1,388	0.72	0.45	0	1
Advised to avoid gatherings	AGA	1,388	0.66	0.47	0	1
Restricted travel within country/area	ITR	1,388	0.34	0.47	0	1
Curfew/lockdown	CFL	1,388	0.45	0.50	0	1
Closure of non-essential businesses	NEBC	1,388	0.32	0.47	0	1
Closure of schools and universities	SCC	1,388	0.35	0.48	0	1
Proportion of hours worked by hired labor	HiredShare	1,115	33%	28%	0%	100%
Share of crops processed and sold	ProcessedShare	1,059	3%	15%	0%	100%
Total land size owned (ha)	Land	1,388	0.85	1.37	0.00	11.29
Value of the livestock (Naira)	LivestockValue	1,388	141,880	532,655	0	12,564,000
Value of assets (Naira)	AssetsValue	1,388	409,670	4,087,887	400	150,169,500
Recipient of a safety net (1 = yes, 0 = No)	SafetyNet	1,388	11%	31%	0%	100%
Normalized Herfindahl–Hirschman Index of income diversification	HHindex	1,317	0.75	0.24	0.12	1.00

2.4.2. Empirical strategy

Let P_{ist}^{m} be a binary variable that takes the value 1 if the household i that resides in state s reported that the policy or measure m was issued in its state or area at period t, and 0 otherwise. As previously explained, this variable captures both the issuance of the policy and the household's awareness. I estimate the average impact of the six policy measures of interest (SAH, AGA, ITR, CFL, NEBC, and SCC) based on the following representation of the change of farm income from the pre-pandemic period ($t = 0$) to the pandemic period ($t = 1$):

$$\Delta\ddot{\Pi}_{is} = \beta_0 + \sum_{m=1}^{6} \beta_1^m \Delta P_{is}^m + \sum_{r=1}^{7} \alpha^r R_{is}^r + \varphi_s + e_{is} \quad (13)$$

where $\Delta\ddot{\Pi}_{is} = \ddot{\Pi}_{is1} - \ddot{\Pi}_{is0}$, $\Delta P_{is} = P_{is1} - P_{is0}$, and $e_{is} = \Delta\epsilon_{is} = \epsilon_{is1} - \epsilon_{is0}$. The variables R^r serve as controls and resilience factors, and α^r are the coefficients associated. φ_s represents the state s fixed effect. The double dot indicates that the farm income is not observed.

Since $P_{is0} = 0, \forall i$ and $\forall s$, ΔP_{is} takes on the value 1 if the policy is issued during the pandemic and 0 otherwise. The coefficients of interest (β_1^m) capture the average effects of the policies m on farm income. They measure the value of $\frac{\partial \Pi^*}{\partial P}$ whose theoretical representation is provided by equation (12). The role of resilience factors is examined by interacting each policy by a vector of resilience factors, i.e., for each policy m:

$$\Delta\ddot{\Pi}_{is} = \beta_0 + \beta_1^m \Delta P_{is}^m + \sum_{r=1}^{7} \alpha^r R_{is}^r + \sum_{r=1}^{7} \gamma_m^r \, \Delta P_{is}^m R_{is}^r + \varphi_s + e_{is} \quad (14)$$

The coefficients of interest are the γ_m^r which capture the role of the resilience factors.

I select the variables R^r so that they serve as control variables (to minimize the selection bias) and resilience factors. For this purpose, I test the presence of systematic differences between the households that were subject to each policy and those that were not using a series of comparisons of means of 31 observable variables using t-tests. Any variable for which the difference between the means is statistically significant is a candidate for the set of controls. In the appendices, I report the means comparisons and the variables' definitions (see appendix A1, tables 26 to 32). In addition, I consider the resilience factors that are extensively employed in the literature (Cissé & Barrett, 2018; FAO, 2016; Smith et al., 2015; Smith & Frankenberger, 2018; TANGO International, 2018; Upton et al., 2020). Hence, I select seven variables based on the necessity to approximate each of the three resilience capacities *to the COVID-19 pandemic*, their role as controls, and the minimization of the correlations between the explanatory variables. As a result, the set of controls and resilience factors includes the value of assets, the total land size owned by the household, the availability of safety nets, the value of the livestock, the normalized Herfindahl–Hirschman Index of income diversification (which indicates the degree of income diversification), the fraction of crops that are processed and sold, and the proportion of labor time that is hired.

I also control for location-specific sources of systematic differences (e.g., climate conditions) by introducing state fixed effects φ_s. The latter also capture inter-state differences in vulnerability to the pandemic, the issuance of policies at the state level (but not households' awareness), and the incidence of the pandemic in the state, which reflects the degree of exposure of the household to the pandemic. This is the best way to approximate the households' exposure because household-level data on that exposure is not available.

There is little concern for endogeneity in this study. The independent variables of interest are indicators of policy shocks, i.e., whether a specific policy was issued by the government. The dependent variables represent, for example, whether the agricultural household income increased. I argue that the government decision to issue a specific policy is exogenous to the household decision making process. Thus, since the household is the unit of analysis, there is little concern for endogeneity. Even though the issuance of the policy is endogenously determined at the country or state levels, this study uses a more disaggregated unit of analysis which can only take as given the decision of the government, especially in the very short run time frame examined in this study. If the unit of analysis were a state or a country, there would be a risk of endogeneity because country level measures of income and policy changes can be both related to unobserved factors. Reverse causality can also be a problem at more aggregate scales of analysis. For example, a substantial decline in the country's level of income (dependent variable) can lead the government to modify its policy (independent variable) to protect the economy.

Considering either the model (13) or (14) and given the unobserved nature of $\Delta\ddot{\Pi}$, I define the following latent variable model:

$$\Delta\ddot{\Pi} = \mathbf{x\Psi} + e, \qquad\qquad y = 1\left[\Delta\ddot{\Pi} > 0\right] \tag{15}$$

whereby the *observed* variable y takes on the value 1 whenever the *unobserved* income change is positive, and 0 otherwise, $1[\cdot]$ being an indicator function. $\mathbf{x}$ is the set of the explanatory variables and $\mathbf{\Psi}$ the set of associated coefficients so that $\mathbf{x\Psi} + e$ is a shorthand for the right-hand side of either the model (13) or (14). Assuming that e is independent of $\mathbf{x}$ and has a standard normal distribution, the response probability of y is:

$$P(y = 1|\mathbf{x}) = P\left(\Delta\ddot{\Pi} > 0\middle|\mathbf{x}\right) = P(e > -\mathbf{x\Psi}|\mathbf{x}) = 1 - G(-\mathbf{x\Psi}) = G(\mathbf{x\Psi}) \tag{16}$$

where G is the standard normal cumulative distribution function (i.e., $G(z) = \Phi(z) = \int_{-\infty}^{z} \phi(v)dv$, where $\phi(v) = (2\pi)^{-\frac{1}{2}} \exp\left(-\frac{z^2}{2}\right)$). Given a sample of size n, the Maximum Likelihood Estimator of $\mathbf{\Psi}$, denoted $\widehat{\mathbf{\Psi}}$, maximizes the log-likelihood $\mathcal{L}(\mathbf{\Psi}) = \sum_{i=1}^{n} l_i(\mathbf{\Psi})$, where $l_i(\mathbf{\Psi}) = y_i \log[G(\mathbf{x}_i\mathbf{\Psi})] + (1 - y_i)\log[1 - G(\mathbf{x}_i\mathbf{\Psi})]$. I then obtain the probit estimate of $\mathbf{\Psi}$.

Furthermore, I cluster the standard errors at the enumeration area level to control for unobservable factors inducing similarities among nearby households.

Finally, I paired the probit models explaining the probability of increased farm income with models explaining its decrease. I also run probit estimations of the impacts on non-farm sources of income, including the nonfarm family businesses and wage employment.

2.5. Results and discussion

This section describes the results concerning the effect of the containment measures on the likelihood that farm and non-farm incomes increase or decrease and highlights how the inter households' heterogeneity in resilience capacities diversely moderated the impact of the shock and made the difference between winners and losers.

2.5.1. Effects of COVID related policies on farm income

2.5.1.1. The average impact of the policies

The results suggest that the stay-at-home advice (**SAH**) and the closure of schools and universities (**SCC**) were beneficial for agricultural households *in the short run*. Indeed, both policies significantly increased the likelihood that farm incomes increased during the pandemic (see Table 2 models 1, 6, and 7). These results draw attention to the fact that the containment measures are not necessarily detrimental for agricultural households. Since farm activities are predominantly home-based and family labor reliant, **SAH** and **SCC** were beneficial because these policies raised family labor availability. The beneficial effect of **SAH** might also result from a rise of some farm products' prices induced by this policy, as the *prices channel* suggests (see theoretical model). This effect through the *prices channel* depends on whether the demand of some farm products increased during the pandemic and the supply elasticity of these farm products. **SAH** and **SCC** may be transformational if the additional benefits they create are reinvested in assets that could improve the household's well-being on the long run.

SAH also significantly reduced the probability that farm income decreased during the pandemic (see Table 3, models 1 and 7), which indicates that it offered the average agricultural household the ability to absorb the negative impact of the pandemic. However, the effect of **SCC** on the likelihood that farm income decreased is not statistically significant. Hence, the results suggest that, while **SAH** and **SCC** provided Nigerian farmers with potential for transformative capacity, **SAH** additionally provided absorptive capacity.

However, I am not able to reject the null hypothesis that other policies had no average impact on the probability that farm income increased or decreased. One may expect that the average agricultural household suffered from the curfews or lockdowns (**CFL**), restrictions of trade within the country (**ITR**), and the advice to avoid gatherings (**AGA**). While the signs of their respective coefficients suggest adverse effects, they are not statistically significant. Non-essential business closure (**NEBC**) should have impacted households that mainly depend on incomes from wage employment, but that is not the case for most agricultural households. Weak compliance of the farmers or other actors of agricultural value chains to these policies may also explain why their average effects are not statistically significant. Nevertheless, these average results mask significant effects on specific groups of agricultural households, as I show in the next section.

The results confirm the distinct nature of agricultural households. While most previous findings stress the overall negative impact of the pandemic on households, my results stress important nuances. The findings also confirm previous ones suggesting that agriculture was relatively more resilient than other sectors but provide detailed evidence per containment measure.

Table 2: Effect of policies on the likelihood that farm income increased

	Dependent variable = 1 if farm income increased, 0 otherwise						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stay-at-home advice	0.145***						0.142***
	(0.0353)						(0.0355)
Avoid gatherings advice		-0.0202					-0.0577
		(0.0380)					(0.0385)
Restrictions of travels within the country			-0.00394				-0.0464
			(0.0388)				(0.0404)
Curfew/lockdown				0.0243			-0.0318
				(0.0405)			(0.0414)
Non-essential business closure					0.0676		0.0407
					(0.0445)		(0.0514)
Closure of schools and universities						0.0976**	0.0943*
						(0.0415)	(0.0535)
Observations	1,008	1,008	1,008	1,008	1,008	1,008	1,008
Pseudo R2	0.114	0.099	0.099	0.099	0.102	0.105	0.122

Notes: This table reports the estimates of the average marginal effects computed based on a probit model. All estimations include a constant, controls variables, state-level fixed effects and are adjusted by cross-section weights. Standard errors are given in parenthesis and are clustered at the enumeration area level. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Effect of policies on the likelihood that farm income decreased

	Dependent variable = 1 if farm income decreased, 0 otherwise						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stay-at-home advice	-0.135***						-0.141***
	(0.0376)						(0.0396)
Avoid gatherings advice		0.0165					0.0390
		(0.0423)					(0.0463)
Restrictions of travels within the country			0.0228				0.0480
			(0.0438)				(0.0437)
Curfew/lockdown				-0.00856			0.0290
				(0.0447)			(0.0430)
Non-essential business closure					-0.0402		-0.0370
					(0.0497)		(0.0526)
Closure of schools and universities						-0.0380	-0.0304
						(0.0562)	(0.0631)
Observations	1,001	1,001	1,001	1,001	1,001	1,001	1,001
Pseudo R2	0.110	0.099	0.099	0.099	0.100	0.100	0.113

Notes: This table reports the estimates of the average marginal effects computed based on a probit model. All estimations include a constant, controls variables, state-level fixed effects and are adjusted by cross-section weights. Standard errors are given in parenthesis and are clustered at the enumeration area level. *** p<0.01, ** p<0.05, * p<0.1

2.5.1.2. The role of resilience capacities

In this section, I examine how the impact of the containment measures varied within the population of agricultural households due to differences in resilience capacities.

The impact of the stay-at-home advice (**SAH)** on the likelihood that farm income increased significantly decreased with the farm size (see Table 4, model 1). The opposite effect is also significant, i.e., the impact of **SAH** on the likelihood that farm income decreased significantly increased with farm size (see Table 4, model 1). Therefore, the beneficial – and potentially transformational – effect of **SAH** was more pronounced among small farmers. Since smallholder farmers rely more on family labor, they benefited more from more family workforce staying at home. In contrast, since larger farms are more dependent on hired labor and thus on the mobility of farm labor, **SAH** hurts them more. Furthermore, since small farmers dominate the agricultural landscape, the average effect of **SAH** is positive and hides the adverse effects on large farmers. Hurting large farmers may be detrimental to the development of export or high-value crops in which they have a non-trivial contribution.

In addition, the share of crops processed and sold significantly increased the effect of **SAH** on the likelihood that farm income increased, but the opposite effect is not significant. Since value addition is an indicator of livelihood diversification which reflects the adaptive capacity (FAO, 2016; Smith et al., 2015; Smith & Frankenberger, 2018; TANGO International, 2018), the results suggest that the more the agricultural household was involved in value addition, the more it was able to adjust to the changing economic environment or seize potential opportunities stemming from the shock. That may be explained by a modification of the composition of the food demand towards more processed or packaged products. A rise in the demand of these products may result in a rise in their prices, which is also beneficial for farmers involved in their production. The weaker dependence of processing activities on the off-household workforce enabled farmers involved in processing to make the adjustments necessary to take advantage of this situation. Hence, the beneficial or transformational effect of **SAH** was also more pronounced among farmers who possess the adaptive capacity offered by value addition capacities. This result demonstrates the interdependence between resilience capacities. Moreover, having more assets significantly decreased the likelihood that **SAH** increased farm income, and the opposite effect is significant. I also find similar results associated with the restrictions imposed on gatherings (**AGA**) (see Table 4, model 2). This means that wealthier farmers tend to be adversely affected by these policies, which is consistent to the fact that they depend more on input (including labor) and outputs markets.

The impact of the restriction of travels within the country (**ITR**) on the likelihood that farm income increased significantly decreased with the degree of livelihood concentration, but the opposite effect is not significant (see Table 4 and Table 5, model 3). Therefore, **ITR** hurt more those with less diversified livelihood. This result is consistent with the adaptive capacity. Since **ITR** disrupted some marketing channels or supply chains, farmers with more adaptive capacity can overcome these disruptions by switching to less disrupted marketing channels. Having more sources of income may also indicate that they have more resources to make the investments that enable them to take advantage of the opportunities stemming from the policy shock.

The impact of curfews and lockdowns (**CFL)** on the likelihood that farm income decreased significantly increased with the proportion of hours worked by hired labor, and the opposite effect is also significant (see Table 4 and Table 5, model 4). These results confirm that movements' restrictions hurt more farms that rely more on agricultural labor markets. The fewer reliance of small farmers on labor markets offers them a greater capacity to absorb the impact of this shock.

In addition, the effect of **CFL** on the probability that farm income decreased significantly increased with the proportion of crops processed and sold, but the opposite effect is not significant. This reflects that **CFL** disrupted processing activities and the transport and distribution of processed foods, which negatively affected processors. It also reduced the demand addressed to farmers by lessening consumers' income. The reduction in the demand of these products may result in a drop in their price, which also hurts farmers. I also find that the impact of **CFL** on the likelihood that farm income increased significantly decreased with the land size. Therefore, **CFL** was more harmful to larger farmers, which is consistent with the consequences of the reduced mobility of agricultural labor. It is also consistent with the fact that larger farmers use to sell a larger share of their products in urban markets while urban households' demand was adversely affected by **CFL**.

I do not find any factors that caused more resilience or more vulnerability to the effects of non-essential businesses closure (**NEBC)** (see Table 4 and Table 5, model 5). This result may be explained by the less involvement of farmers in this form of businesses relative to urban and rural non-farm households and the less compliance to **NEBC** in rural areas.

The effect of **SCC** on the likelihood that farm income decreased was significantly higher for those having less diversified sources of income (see table Table 5, model 6). Therefore, **SCC** hurt more those who rely on fewer sources of revenue. Therefore, households benefited more from having alternative livelihood strategies to which they may allocate the additional labor that stems from **SCC**.

Table 4: Role of resilience factors in the likelihood that farm income increased

	Dependent variable = 1 if farm income increased, 0 otherwise					
POLICY	(1) Stay-at-home advice	(2) Avoid gatherings advice	(3) Restrictions of travels within the country	(4) Curfew/ lockdown	(5) Non-essential business closure	(6) Closure of schools and universities
POLICY	0.183	0.0345	0.275**	0.0881	0.157	0.274*
	(0.144)	(0.134)	(0.136)	(0.134)	(0.145)	(0.161)
POLICY×HiredShare	-0.113	-0.0736	-0.0143	-0.236*	-0.0886	0.0210
	(0.145)	(0.140)	(0.153)	(0.121)	(0.137)	(0.147)
POLICY×ProcessedShare	0.399*	-0.0182	0.0858	-0.0999	-0.139	0.186
	(0.204)	(0.210)	(0.222)	(0.181)	(0.260)	(0.276)
POLICY×Land	-0.0924**	-0.0249	-0.0327	-0.0748**	-0.0511	-0.0121
	(0.0373)	(0.0349)	(0.0244)	(0.0320)	(0.0312)	(0.0315)
POLICY×LivestockValue	1.46e-07	5.63e-08	-4.41e-08	1.16e-07	8.69e-08	1.41e-08
	(1.46e-07)	(1.34e-07)	(8.82e-08)	(8.29e-08)	(8.75e-08)	(9.11e-08)
POLICY×AssetsValue	-1.06e-07*	-1.93e-07***	9.03e-09	3.03e-08	-8.10e-08	-4.01e-08
	(5.40e-08)	(6.54e-08)	(5.13e-08)	(3.92e-08)	(5.85e-08)	(5.55e-08)
POLICY×SafetyNet	-0.164	-0.186	-0.0613	-0.0234	-0.00844	-0.116
	(0.134)	(0.138)	(0.109)	(0.0982)	(0.117)	(0.114)
POLICY×HHindex	0.115	0.0712	-0.312*	0.116	0.0191	-0.208
	(0.172)	(0.149)	(0.164)	(0.141)	(0.175)	(0.170)
Observations	1,008	1,008	1,008	1,008	1,008	1,008
Pseudo R2	0.131	0.110	0.107	0.115	0.109	0.109

Notes: This table reports the estimates of the average marginal effects computed based on a probit model. All estimations include a constant, controls variables, state level fixed-effects, and are adjusted by cross-section weights. Standard errors are given in parenthesis and are clustered at the enumeration area level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Role of resilience factors in the likelihood that farm income decreased

POLICY	(1) Stay-at-home advice	(2) Avoid gatherings advice	(3) Restrictions of travels within the country	(4) Curfew/ lockdown	(5) Non-essential business closure	(6) Closure of schools and universities
	Dependent variable = 1 if farm income decreased, 0 otherwise					
POLICY	-0.148	-0.0798	-0.272*	-0.254*	-0.361**	-0.346*
	(0.156)	(0.148)	(0.153)	(0.142)	(0.157)	(0.177)
POLICY×HiredShare	0.0486	0.133	0.146	0.476***	0.257	0.149
	(0.157)	(0.156)	(0.151)	(0.146)	(0.164)	(0.166)
POLICY×ProcessedShare	-0.231	-0.0599	0.0965	0.408*	0.314	-0.0118
	(0.257)	(0.195)	(0.257)	(0.226)	(0.294)	(0.321)
POLICY×Land	0.122***	0.0564	0.0192	0.0493	0.0429	0.000857
	(0.0389)	(0.0355)	(0.0281)	(0.0333)	(0.0331)	(0.0362)
POLICY×LivestockValue	-1.96e-07	-1.74e-07	3.99e-08	-1.26e-07	-1.04e-07	-3.61e-09
	(1.55e-07)	(1.58e-07)	(8.91e-08)	(1.01e-07)	(1.02e-07)	(1.06e-07)
POLICY×AssetsValue	1.16e-07*	2.77e-07***	-1.55e-08	-4.72e-08	-9.95e-09	1.30e-08
	(6.88e-08)	(8.53e-08)	(5.71e-08)	(5.27e-08)	(6.03e-08)	(5.64e-08)
POLICY×SafetyNet	0.130	0.211	-0.00583	-0.0451	-0.0472	0.00656
	(0.154)	(0.155)	(0.117)	(0.116)	(0.138)	(0.135)
POLICY×HHindex	-0.151	-0.0728	0.290	0.0585	0.255	0.338*
	(0.180)	(0.170)	(0.177)	(0.143)	(0.173)	(0.182)
Observations	1,001	1,001	1,001	1,001	1,001	1,001
Pseudo R2	0.124	0.115	0.105	0.123	0.113	0.107

Notes: This table reports the estimates of the average marginal effects computed based on a probit model. All estimations include a constant, controls variables, state level fixed-effects, and are adjusted by cross-section weights. Standard errors are given in parenthesis and are clustered at the enumeration area level. *** p<0.01, ** p<0.05, * p<0.1

2.5.2. Average effects of containment measures on nonfarm income

The results presented in appendix A1 (tables 33 to 36) suggest that **SCC** significantly increased the likelihood that non-farm businesses' income increased and the opposite effect is significant. Therefore, non-farm businesses also benefited from the additional labor stemming from **SCC**. **NEBC** significantly increased the likelihood that non-farm businesses' income increased and the opposite effect is significant. This may reflect a reallocation of resources from off-households non-farm to within-household non-farm businesses because the former are more likely to be disrupted. **AGA** significantly raised the likelihood that the non-farm businesses' income decreased during the pandemic, which can be explained by the less frequentation of markets for nonfarm products. **SAH** significantly reduced the likelihood that businesses' income decreased which confirms the reallocation of resources towards domestic activities.

Concerning wage employments, I find that **AGA** decreased the likelihood that their income increased, with significant opposite effect. These results reflect the loss of jobs or reduction in wages associated with employments along food supply chains.

2.6. Conclusion and policy implications

Decision-makers took severe and urgent measures to contain the spread and human costs of the COVID-19 pandemic, which went from a local outbreak in China to a global pandemic in a matter of months. While these measures were somewhat effective from a health perspective, the results of this study confirm previous ones which contend that they are harmful from a socio-economic perspective. However, this study adds an important nuance in the sense that while some policy responses harmed agricultural households, others are beneficial for some types of agricultural households. It also nuances in terms of differential impacts across sources of farmers' income.

The findings contribute to an evidence-based improvement of policy responses to the COVID-19 pandemic and similar upcoming health shocks. Since these policies must protect human health but also households' socio-economic conditions, it is important to identify their beneficial and adverse effects, and in each case, which type of household is affected, and understand why? As the World Bank aptly put it, “the economic crisis requires a parallel and simultaneous effort to save jobs, protect income, and ensure access to services for vulnerable populations” (World Bank, 2020).

The study also contributes to the improvement of strategies aimed at building individuals’, households’, and communities’ resilience to various forms of shocks or stressors, by providing evidence of the role of resilience factors in the COVID-19 context. It is then of high value to decision-makers and NGOs that increasingly employ the resilience approach in their development projects and programs and are permanently in the process of improving their resilience approach using the output from scientific research. While the resilience factors considered as part of this study can only be improved over a long period, one also need to understand how to improve resilience in the short run. For instance, income support measures were proven to protect food security during the pandemic (Nechifor et al., 2021). Many African countries also resorted to their National Strategic Grain Reserves to protect the poor from food insecurity (Nhemachena & Murwisi, 2020; Sihlobo et al., 2021). However, the effectiveness of such short-term responses depends on the ability to actually reach the poor.

The disruptions of many activities in the secondary and tertiary sectors are not without implications for structural transformation. Some authors have already noticed that labor was moving from outside to inside the agriculture sector during the pandemic. This movement may exacerbate the level of poverty (by reducing the agricultural value-added per worker) and limit the ability of the whole economy to bounce back to the pre-pandemic pattern of structural transformation if the farm sector is not sufficiently resilient to a drop in farm revenues. In this sense, this study provides a beginning of an understanding of the potential long-term implications of this pandemic.

Finally, more research is needed to inform policy makers and other stakeholders to development projects or programs. As previously mentioned, examining the long-term effects of these policy responses will be of high value. In addition, a more comprehensive view of the impact of the pandemic from the resilience lenses requires the research community to dig into the resilience capacities associated with each nonfarm activity in which the farmer may be involved.

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CHAPTER 3. ESSAY 2: SHOCKS, RESILIENCE, PRODUCTIVITY, AND AGRICULTURAL TRANSFORMATION: A DYNAMIC APPROACH

3.1. Introduction

Scholarly inquiry into and policy interest in the measurement of agricultural productivity, associated growth trends, and the implications for the agricultural and other sectors of the economy go back at least seven decades (Christensen, 1975; Cooper et al., 1947; Hayami, 1969; Johnston & Mellor, 1961; Lewis, 1954; Ranis & Fei, 1961; Timmer, 1988). The extant literature highlights the roles of agricultural productivity in economic growth, economic transformation, and overall development (Johnston & Mellor, 1961; Lewis, 1954; Ranis & Fei, 1961; Timmer, 1988). The link between agricultural productivity and economic growth is particularly strong in the case of developing countries, where agriculture typically occupies a large share of the gross domestic product (GDP) (Gollin, 2010). In these countries, productivity shocks in the agricultural sector are almost always associated with reductions in overall economic growth rates (Acevedo et al., 2020; Barrios et al., 2008, 2010).

Productivity growth has been shown to account for a large share of long-term per capita income growth (Easterly, 2001; Hall & Jones, 1999; Kendrick, 1961; Prescott, 1998). The strand of the extant economic literature that examines the contribution of the agricultural sector to economic development identified positive linkages between agricultural productivity, economic transformation, and economic growth and considers agricultural transformation as an essential component of the economic transformation process (Johnston & Mellor, 1961; Lewis, 1954; Ranis & Fei, 1961; Timmer, 1988). Indeed, economic transformation – the combination of the shift of economic resources from low- to high-productivity sectors and faster productivity growth in the main sectors of the economy – is a key driver of living standards and resilience (Jayne et al., 2021). Agricultural transformation represents the shift from a subsistence-oriented and farm-centered farming system into a more commercialized, productive, and off-farm centered (see Jayne et al., 2018; Timmer, 1988). Furthermore, productivity gains in the agricultural sector are key drivers of the agricultural transformation process (Timmer, 1988). As agriculture is a main sector in sub-Saharan African countries, agricultural productivity gains are a critical factor of both their agricultural and economic transformations (Jayne et al., 2021).

A long-term agricultural productivity growth trend is typical for developing countries (Benin, 2016; Rosegrant & Evenson, 1992). This is attributable to the contributions of multiple factors, including high returns to investments in research and development (R&D), soil and climate-related factors, political and institutional factors, agricultural policies, trade, education, innovation, and level of income (Fulginiti et al., 2004; Hall & Jones, 1999; Headey et al., 2010; Liu et al., 2020; Michler, 2020; Miller & Upadhyay, 2000). For instance, R&D enables technological change through innovations along the entire agricultural value chain (Reardon et al., 2019), including the development of new seeds, which are typically aimed at improving crops' yields or resilience. An illustration of the role of institutions is the household production responsibility system in China which improved farmers' allocation of resources and productivity (Fan, 1991).

While recent studies on agricultural productivity continue to validate the relevance of previously identified drivers of agricultural productivity, some studies suggest the emergence and importance of newly relevant drivers. For example, the growing incidence and frequency of factors previously thought to be extraneous factors and their socio-economic consequences raise some concerns about how extraneous these factors truly are. Specifically, shocks (including terrorism and other conflicts; epidemics and other health shocks; droughts, floods, and other natural disasters; and climate change (CRED & UNISDR, 2020) can no longer be considered as extraneous factors in the modeling of economic growth and the economic transformation processes.

In light of the above, a recent strand of the development literature questions the direct impacts of shocks on economic growth (Acevedo et al., 2020; de Groot, 2010; Novta & Pugacheva, 2021). At the same time, studies at the micro-scale provide early answers as to the channels through which these shocks harm agricultural productivity and economic growth. For instance, conflicts limit farmers' access to arable lands, limit their access to hired farm labor, and diminish agricultural outputs (Adelaja & George, 2019a, 2019b). The impacts on output and inputs being disproportional, one expects direct impacts on productivity measures. Similarly, the COVID-19 pandemic was associated with reduced labor market participation and earnings, among several reported adverse human and health effects (Amare et al., 2021; Gupta et al., 2021; Mahmud & Riley, 2021). These have implications for labor and other productivity measures. Furthermore, given that better nutrition quality or health conditions were proven to enhance labor productivity (Bliss & Stern, 1978; Croppenstedt & Muller, 2000), shocks like armed conflicts may indirectly impact agricultural productivity by reducing the degree of food security, as demonstrated by George, Adelaja, and Weatherspoon (2020).

Despite these previous contributions, much remains to be understood as to how shocks affect productivity growth and economic transformation. An appropriate starting point for inquiry into the role of shocks in economic growth is through a deeper analysis of the effects through productivity. This is because, as the first paragraph indicates, productivity is perhaps the most appropriate variable for tracking the paths of economic growth and transformation (Christensen, 1975; Cooper et al., 1947; Hayami, 1969; Johnston & Mellor, 1961; Lewis, 1954; Ranis & Fei, 1961; Timmer, 1988). It was developed by economists as a metric for tracking and measuring growth, and it provides a robust framework for simultaneously evaluating efficiency gains in the uses of all factors of production. Furthermore, given the central role of productivity measurement in studying development, the limited number of studies examining the impacts of shocks on productivity is concerning.

In the context of developing countries, short-term economic growth rates are closely related to agricultural growth rates, which, in turn, are affected by productivity shocks (e.g., rainfall shocks or fluctuations). When it comes to economic transformation, long-term positive (negative) trends in the productivity of inputs indicate improvements (degradation) of the quality of inputs employed. Since trends in the quality of inputs indicate how the structure of agricultural production is transforming over time, examining the effects of shocks on the short- and long-term paths of agricultural inputs' productivities amounts to study how shocks influence the structure of agricultural production, which is itself a key indicator of overall economic transformation, especially in developing countries.

Based on the above, this essay investigates the impacts of two types of shocks (conflicts and droughts) on the short- and long-term trajectories of agricultural productivity in sub-Saharan African countries. Previous papers which have attempted to examine how these shocks affect agricultural productivity utilized a short-term perspective (e.g., Appau et al. 2021; Fulginiti et al. 2004; Ferreira et al. 2010; Mugizi and Matsumoto 2021). While their results confirm the expected adverse effects of shocks on productivity, they do not consider the long-term perspective since they were not explicitly interested in economic transformation. Consequently, these studies did not say much about how shocks affect short- and long-run patterns in the quality of inputs used, even less how the shocks affect the transformation of the structure of agricultural production over time. In addition, concerning productivity measures, they were limited to specific factor productivity measures such as labor productivity, aggregated capital productivity, and total factor productivity. Here, it is argued that a comprehensive examination of the transformation of the agricultural production structure requires the consideration of the productivities of all inputs, including labor, land, machinery, fertilizer, seeds, and other inputs for which data exists.

To fill the above-referenced gaps in the literature, this essay studies the short- and long-term impact of two types of shocks (namely conflicts and droughts) on the paths of inputs productivities and total factor productivity in sub-Saharan African countries and considers all the relevant inputs that enter into the agricultural production system. Thus, the analysis enables one to examine the differential impacts across shocks. It also allows one to see which inputs' productivity measures are more impacted and how these impacts relate to total factor productivity. To achieve these purposes, the growth rates of factor productivities and total factor productivity are first computed at the country level in sub-Saharan Africa using a growth accounting procedure. Next, an infinite distributed lag model is used to estimate the short- and long-term effects of conflicts and droughts on these productivity measures and to examine the time required to revert back to pre-shock growth rates of the productivity measures. Last, the effects of these shocks on the degree of technical efficiency is examined through Data Envelopment Analysis (DEA) and Tobit models.

The extent to which a shock affects the welfare or performance of economic units (i.e., individuals, households, communities, firms, and countries) depends on the ability of these units to withstand the shock and quickly bounce back to pre-shock level in the aftermath of the shock. In some cases, shocks can indeed result in improved trajectories, which is the essence of the concept of building back better transformation ability. For this reason, the research question in this study is also related to the resilience literature (Adelaja et al., 2020, 2021; Arouri et al., 2015; Barrett & Constas, 2014; Breisinger et al., 2014; Cissé & Barrett, 2018; Smith et al., 2015). This essay contributes to the resilience literature by introducing a new approach to measuring resilience based on the relative amplitude of the shocks' short- and long-term effects on agricultural productivity and the time required to bounce back. This contribution is essential because resilience is intrinsically a dynamic concept, but the current resilience measures tend to proxy macro-economic resilience by using a set of static characteristics specific to the economic unit and its environment (social, economic, political, institutional, infrastructural, etc.) (e.g., Smith et al. 2015; FAO 2016). Hence, examining how shocks disrupt short- and long-term trajectories of partial and total factor productivities also allows the measurement of the degree of resilience from a dynamic perspective.

The rest of this essay is organized as follows. Section 2 provides a detailed background on the drivers of economic growth, the negative role of shocks in shifting production structure and impeding the growth process, the possible role of resilience factors in mitigating the adverse effects of shocks, and the relationship between partial and total factor productivity indexes. Section 3 presents a theoretical model for understanding the nexus between shocks, resilience, productivity, and components of productivity. Section 4 presents details on the empirical analysis, including data sources, productivity, and technical efficiency measures, and approaches for shocks' impact estimation. Finally, section 5 presents the empirical results, while section 6 presents the summary, conclusion, and policy implications.

3.2. Background

3.2.1. Drivers of economic growth

Early theories on economic growth focus on the role of savings and capital and their accumulation. For Ramsey (1928) and Solow (1956), economic growth is driven by the investment of household savings in capital accumulation. In the Lewis (1954) model, economic growth is driven by the reallocation of excess labor from the traditional sector (e.g., agriculture) to the modern sector (e.g., manufacturing) and the expansion of the modern sector through savings to finance capital accumulation. Prebisch and Singer suggest that economic growth should be fostered by import substitution strategies, temporary protection of nascent industries, and technical progress in primary production (Prebisch, 1950; Singer, 1950).

Later, the rise of endogenous growth theory placed emphasis on the endogeneity of the macro drivers of economic growth. Technological change is argued to be a key driver of economic growth (Grossman & Helpman, 1994; Romer, 1990). Several authors argued that investment in education and thereby in human capital accumulation stimulates innovation, technological diffusion, productivity gains, and thus economic growth (Azariadis & Drazen, 1990; Barro, 1996; Becker, 1975; Lucas, 1988; Nelson & Phelps, 1966; Romer, 1990; Schultz, 1961). Investments in R&D, the macroeconomic environment, trade openness, and the development of financial markets are also important for growth (Bassanini et al., 2001). Others add to this literature by demonstrating the role of improvements in nutrition and health in driving productivity gains and thus economic growth (Bliss & Stern, 1978; Kalemli-Ozcan et al., 2000; Strauss & Thomas, 1998; Weil, 2007). Backward linkages (i.e., an investment creates or generates additional demand for inputs) and forward linkages (i.e., an investment stimulates the demand for its outputs either in the form of final consumption or intermediary consumption) introduced by Hirschman (1992) also drive economic growth.

The role of trade and FDIs was also highlighted in the literature. The Export-Led-Growth theory contends that export-enhancing trade policies stimulate economic growth (Awokuse, 2003; Marin, 1992; Richards, 2001; Wilbur & Haque, 1992; Awokuse, 2003; Yamada, 1998). This theory argues that exports stimulate growth through efficient use of resources and capital accumulation. Foreign exchanges generated from exports are invested in the imports of capital goods, which drives capital accumulation. The Import-Led-Growth theory contends that importing more advanced technologies in the form of capital goods stimulates innovation, productivity, and subsequently economic growth (Awokuse, 2008; İşcan, 1998; Lawrence & Weinstein, 1999; Marwah & Tavakoli, 2004). FDIs stimulate economic growth through physical capital and human capital accumulation, technological improvements, and diffusion (Balasubramanyam et al., 1996, 1999; Borensztein et al., 1998; de Mello, 1999; Li & Liu, 2005; Obwona, 2001).

3.2.2. The roles of shocks and resilience factors

Shocks alter the processes of economic growth and transformation through their effects on the micro- and macro- growth drivers. Specifically, these shocks may affect the demand for outputs, the supply and/or demand of inputs, and/or the productivities of inputs. For example, the COVID-19 pandemic, storms, floods, and droughts were all associated with reductions in households' earnings (Arouri et al., 2015; Gupta et al., 2021), which may result in reduced derived demand for outputs. The COVID-19 pandemic was also associated with a reduced supply of inputs, primarily labor (Amare et al., 2021). Conflicts were associated with reduced demand for inputs, especially the demand for hired labor in agriculture (Adelaja & George, 2019a) and the demand for land through farmland abandonment (Adelaja & George, 2019b). They were also associated with a "forgetting by not doing effect" which decreases the stock of knowledge in the economy (Collier & Duponchel, 2013). Conflicts and natural disasters cause large population forced displacements, which reduce labor supply in affected areas. A significant drop in labor supply may create a recession in affected areas.

The channels through which shocks affect inputs' productivities include (a) the alteration of savings behavior (evidenced in the case of COVID-19 by Mahmud & Riley, 2021), which might reduce the ability to invest in more productive inputs, (b) disruptive effects on the supply and demand of skilled and low-skilled workers due to forced displacement (Verme & Schuettler, 2021), and (c) adverse effects on schooling and thereby human capital accumulation (Paudel & Ryu, 2018). In addition, since nutrition quality or health conditions induce higher labor productivity (Bliss & Stern, 1978; Croppenstedt & Muller, 2000), armed conflicts impact agricultural productivity by reducing the degree of food security, as demonstrated by George, Adelaja, and Weatherspoon (2020). Hence, the evidence suggests that shocks adversely affect economic growth through their short and potentially long-term effects on several growth drivers.

For any economic unit, the trajectory of an economic performance indicator (e.g., a country's agricultural output) is expected to be disrupted when a shock occurs. As illustrated in Figure 4, this disruption has two key characteristics: (1) the extent of the deviation from the normal (without shock) trajectory (hereafter called Δ); and (2) the time required for the unit to return the normal (without shock) level of performance (hereafter referred to as τ). A high Δ is likely to lead to a longer τ. Δ and τ are two characteristics embodied in the concept of resilience. Generalizing the framework presented by Adelaja et al. (2021), it is contended that, on one extreme, a unit is very resilient to a specific shock if Δ and τ are small. On the other extreme, the unit is non-resilient if Δ and τ are very high, which means that the unit endures a significant and possibly permanent deviation from its normal performance trajectory. Between the two extremes, several degrees of resilience are possible. These are defined by the set $(\Delta, \tau), \Delta \geq 0, \tau \geq 0$. Moreover, an economic unit may endure several shocks simultaneously, which complexifies the analysis.

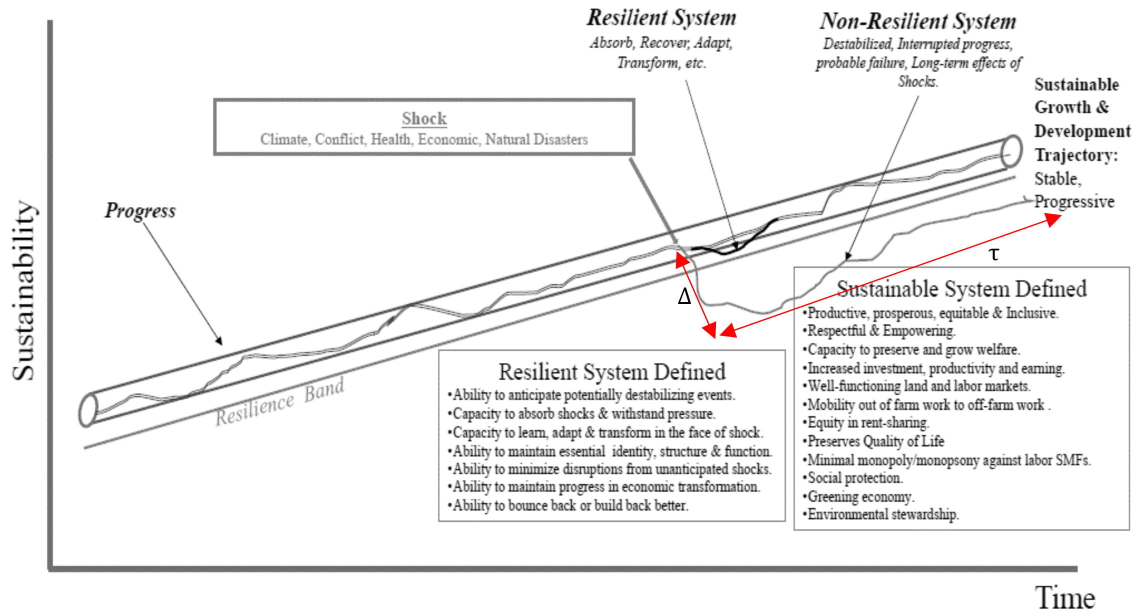

Figure 4: Hypothetical performance trajectory
Source: Adapted from (Adelaja et al., 2021)

Next, consider a real example in Figure 5 which shows the trajectory of the agricultural output index in Nigeria. The agricultural output growth is a major component of economic growth in developing countries. The trend line in red represents the normal trajectory while the dashed lines represent acceptable deviations from the trend. Acceptable deviations above the trend are computed by adding to (or subtracting from) the trend's value one standard deviation of the series of deviations about the trend. I consider a shock 'severe' if it leads to an agricultural output index that wanders beyond the band delineated by the acceptable deviations. The vertical red lines identify the period 2008-2014. One can observe the disruptions caused by multiple climate shocks, including droughts (Durowoju et al., 2022; Shiru et al., 2018).

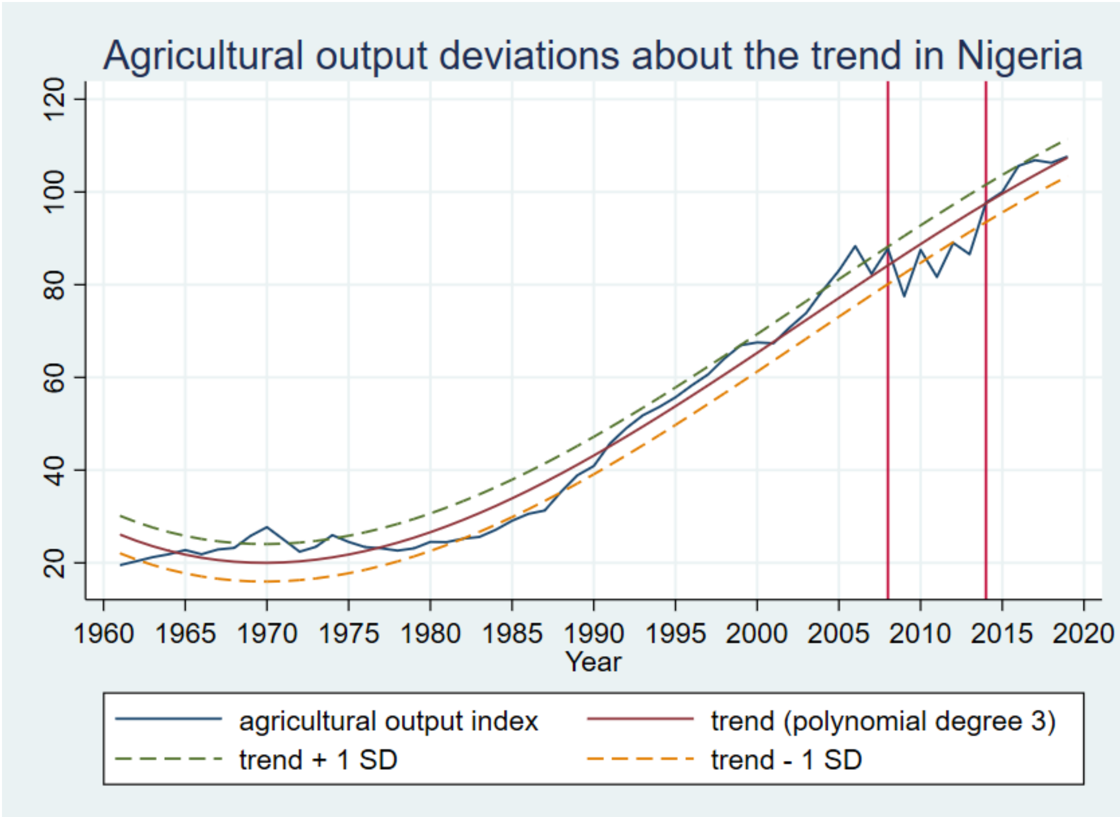

Figure 5: Evolution of the agricultural output in Nigeria
Source: authors calculations based on the USDA-ERS dataset

3.2.3. Total factor productivity and the structure of agricultural production

A partial productivity measure is the ratio of output and a specific input quantities and indicates the quantity of outputs obtained per unit of the input. An increase in the partial productivity associated with some input indicates a more proper use of that input or the use of a better quality of that input. For instance, greater labor productivity may result from improved health and nutrition of human resources (i.e., quality of the labor input) (Bliss & Stern, 1978; Croppenstedt & Muller, 2000), better management of human resources, or improvement of the technical skills of the human resource. Similarly, a greater output per unit of seed results from either the use of improved seeds or better compliance with the technical recommendations provided by extension agents. Changes in the productivity of seeds may reflect changes in the availability of improved seeds, their use by farmers, the coverage of extension services, and farmers' compliance with the advice provided by the extension agents. These examples, which can be extended to the use of fertilizers, machinery, land, livestock, and other agricultural inputs, help illustrate how tracking the productivity of inputs enables one to examine the changing structure of agricultural production.

Partial measures of productivity can be misleading when assessing the productivity of the overall production system (Coelli et al., 2005). For such purposes, the preferred measure is the total factor productivity (TFP), defined as the ratio of aggregate outputs to aggregate inputs. TFP indicates the quantity of output that an economic unit produces using the current combination of all inputs. The growth of TFP indicates improvements in the ability to combine inputs more productively, changes in the quality of inputs (including skills and embedded technology), changes in the stock of technological knowledge, changes in organizational methods, access to information, and institutional environment (Barro, 1999; Herzer, 2021; Hulten, 2001; Vandenberghe, 2017).

The productivity level of an economic unit depends on its degree of Technical Efficiency (i.e., the degree of departure from the production frontier), exploitation of Scale Economies (i.e., the distance from the technically optimal scale of operations), and Allocative Efficiency in input selection (i.e., the ability to choose the mix of inputs that produces a given quantity of outputs at minimum cost) (Coelli et al., 2005). From a dynamic perspective, the change in TFP depends on the changes in TE, SE, and AE, but also on the shift of the production frontier, which is referred to as Technical Change (Coelli et al., 2005; Fan, 1991).

Technical Efficiency indicates the degree of adoption of the best practices available. It reflects the extent to which the technical choices implemented by the manager of the economic unit are distant from the best possible choice available and is frequently associated with entrepreneurial and managerial skills, levels of managerial efforts, access to knowledge, and managers' stock of knowledge (Kirkley et al., 1998; Müller, 1974; Page, 1980). Therefore, TE assesses the production structure in the sense that it provides information on the extent of improvements that are still doable by improving the management of the productive unit.

3.3. Theoretical model

3.3.1. Impact of shocks on productivity

In this section, I provide a theoretical model that explains how a shock affects the production performances of economic units, including their output, productivity, and technical efficiency. It also explains the distribution of these impacts across economic units.

Consider a world where there are one input and one output and let $y = (x, q) \in \mathbb{R}^2$ where $x \geq 0$ and $q \geq 0$ are the input and output related variables, respectively. A shock can have two effects: (1) it can reduce the quantity of input that is available (for instance, a drought reduces the amount of water available to farmers; a conflict reduces farmers' accessibility to arable lands and inorganic fertilizers) or (2) it can reduce the quality of input that is available (for instance, the COVID-19 pandemic was associated with a drop in the availability of quality inputs, including seeds and fertilizers, and a rise in the sale of poor quality inputs). It can also have both effects simultaneously. When considering the effect (1), the variable x refers to the quantity of the input and q while the quantity of output produced. When considering the effect (2), the variable x refers to an index of the quality of the input whose level increases with the quality of the input, and q refers to the output quantity per unit of input. In either case, $f(x)$ denotes the transformation frontier, and the production set is $Y \subset \mathbb{R}^2$. Formally, $Y = \{(x, q) \in \mathbb{R}^2 : q - f(x) \leq 0, (x, q) \geq 0\}$.

Figure 6 shows both cases in the same graph, along with an *inefficient* economic unit operating at the point $A = (x_1, P_1)$ before the shock. The productivity of the economic unit is represented by the slope of OA. The extent of its input-oriented and output-oriented technical inefficiencies are represented by AP_2 and AP_5, respectively. The effect of the shock is represented by the variable $s > 0$. s represents the upper limit imposed by the shock on the quantity or quality of inputs that the firm may use when considering effects (1) and (2), respectively. s is inversely related to the intensity of the shock (i.e., as the severity or intensity of the shock increases, s decreases). In presence of the shock, the economic unit must choose a level of input x such that $x \leq s$, which is no longer the case of the point A. As a result, it may move to points A_1, A_2, A_3, or A_4 for instances.

First, I study the impacts of these four non-exhaustive moves on productivity. Considering effect (1), a move from A to A_1 or A_4 increases the productivity level. This is indicated by the steeper slope of OA_1 and OA_4 relatively to OA's slope. However, a move from A to A_2 or A_3 reduces productivity. Considering effect (2), a move from A to A_1, A_2, or A_3 decreases the productivity while a move to A_4 increases productivity. Therefore, for an *inefficient* economic unit, the shock may increase or decrease productivity. To study the distribution of these productivity impacts across firms, assume that A, A_1, A_2, A_3, and A_4 represent five different economic units. Because x_2, x_3, and x_4 are smaller than s while x_1 is greater than s, only the economic unit A must reduce the level of x while the other units do not have to.

Second, I examine the impacts on technical efficiency, focusing on input-oriented technical inefficiency. A move from A to A_1 or A_4 decreases the extent of technical inefficiency because $AP_2 > A_4P_6$ and $AP_2 > A_1P_7$. A move from A to A_2 increases the extent of technical inefficiency because $AP_2 < A_2P_4$. However, a move from A to A_3 does not change the extent of technical inefficiency since $AP_2 = A_3P_4$. Therefore, for an *inefficient* economic unit, the shock may increase or decrease in the technical efficiency level. The distribution across economic units of the impacts on technical efficiency is similar to the one discussed in the previous paragraph.

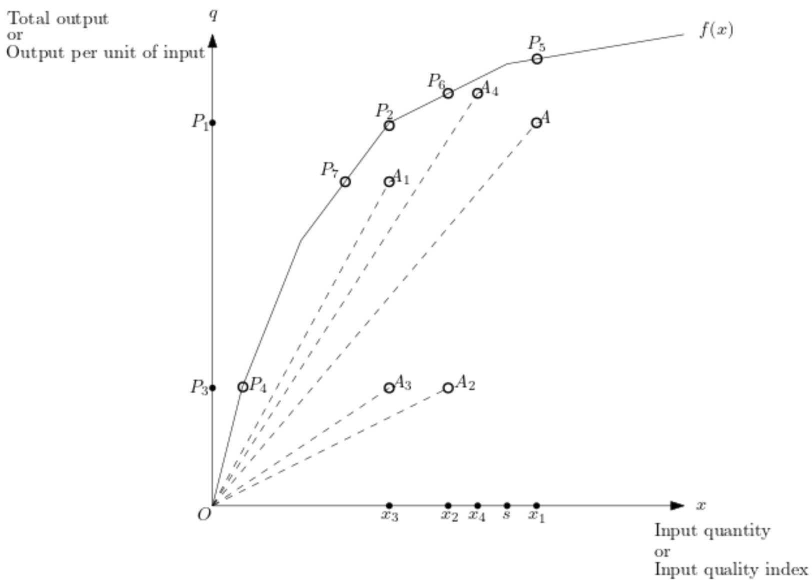

Figure 6: Effect of a shock on productivity and technical efficiency

One can examine the effect of the shock on an *efficient* firm operating in perfect competitive markets for inputs and outputs using a profit maximization problem (PMP). For such purpose, I extend the model to allow for M inputs of quantities $\boldsymbol{X} = (x_1, \dots, x_M)$ and a single output of quantity q. Each input m is associated with a variable s_m which represents the upper limit imposed by the shock on the level of m. As s_m decreases, the constraint imposed by the shock on the input quantity or quality available is more important. The value of s_m is exogenously determined by $s_m = H_m(E)$ where E represents the exposure to the shock and H_m is a m-specific decreasing function of E, representing how the shock contracts the quantity or quality of input m available. Let $\boldsymbol{w} = (w_1, \dots, w_M)$ denote the vector of input prices and p the price of the output.

The PMP is:

$$\max_{\boldsymbol{X} \geq 0} pf(\boldsymbol{X}) - \boldsymbol{wX} \tag{17}$$

$$s.t. (x_1, \dots, x_M) \leq (s_1, \dots, s_M) \tag{18}$$

Solving the PMP yields the optimal value of X written $X^*(p, \boldsymbol{w}, \boldsymbol{S})$, where $\boldsymbol{S} = (s_1, \dots, s_M)$ and the optimal production $q^* = f(X^*) = q^*(p, \boldsymbol{w}, \boldsymbol{S})$. The effect of a rise in the exposure to the shock (E) is:

$$\frac{\partial q^*}{\partial E} = \frac{\partial q^*}{\partial p}\frac{\partial p}{\partial E} + \sum_{m=1}^{M} \frac{\partial q^*}{\partial w_m}\frac{\partial w_m}{\partial E} + \sum_{m=1}^{M} \frac{\partial q^*}{\partial s_m}\frac{\partial s_m}{\partial E} \tag{19}$$

$\frac{\partial q^*}{\partial p}\frac{\partial p}{\partial E} = \sum_{m=1}^{M} \frac{\partial q^*}{\partial w_m}\frac{\partial w_m}{\partial E} = 0$ if the shock has no impact on input and output prices. $\sum_{m=1}^{M} \frac{\partial q^*}{\partial s_m}\frac{\partial s_m}{\partial E}$ represents the effect of the shock on the optimal output through its effect on the quantity or quality of input available. $\frac{\partial s_m}{\partial E} \leq 0$ because H_m is a decreasing function of E. $\frac{\partial q^*}{\partial s_m} = \sum_{l=1}^{m} \frac{\partial q}{\partial x_l}\frac{\partial x_l}{\partial s_m} \geq 0$ because, as explained previously, as s_m decreases, the firm may have to reduce the level of x that it uses (so $\frac{\partial x_l}{\partial s_m} \geq 0$) and $\frac{\partial q}{\partial x_l}$ represents the marginal productivity of input l which is positive. Note that I assume that the cross partial effects are also positive, i.e., reducing s_m has no effect on x_l for $m \neq l$. Thus, $\frac{\partial q^*}{\partial s_m}\frac{\partial s_m}{\partial E} \leq 0$, which means that, assuming no effect on prices, the shock is expected to decrease the output. In the presence of effects on prices, the latter must be accounted for. Note that the PMP results only fit an efficient firm, but not for an inefficient firm. Inefficiencies result from market failures and constraints that lead the economic unit to not produce at the frontier.

3.3.2. A dynamic view of resilience

The role of resilience factors can now be formally represented using utility theory. Consider Figure 7 and Figure 8 below, which represent the two extremes of resilience (absolute non-resilience and absolute resilience). The black curves represent the trajectory of the welfare function $W(X(s), t)$ in the absence of any shock while the red curves represent the actual trajectory, i.e., in the presence of the shock. X is a vector of the unit's socio-economic, institutional, and other characteristics that may determine the level of welfare. The shock (s) is assumed to affect the levels of these characteristics. t represents the time period.

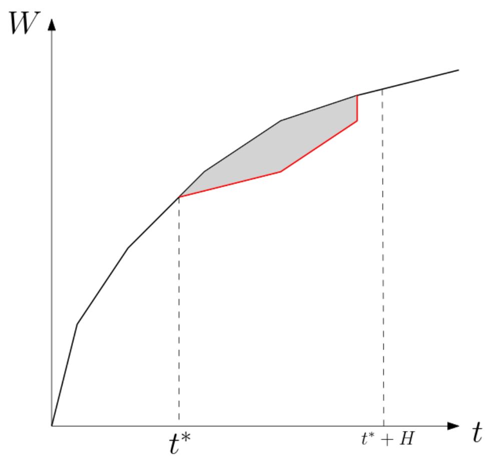

Figure 7 : Resilient unit

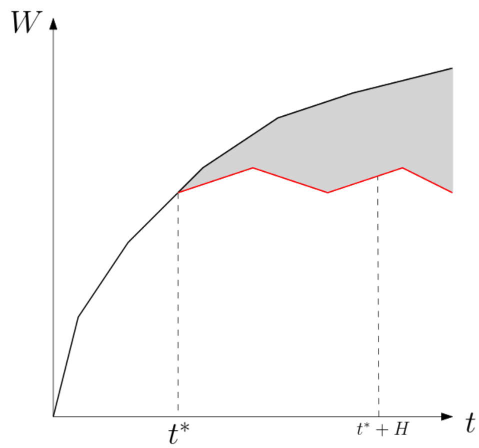

Figure 8: Non-resilient unit

Assuming that a specific shock occurred at t^*, the cumulative welfare loss measured at some time $t > t^*$is:

$$\ell(t) = \int_0^t W(X(0), t)dt - \int_0^t W(X(1), t)dt \tag{20}$$

$$\ell(t) = \int_{t^*}^t W(X(0), t)dt - \int_{t^*}^t W(X(1), t)dt \tag{21}$$

$\ell(t)$ is the value at time t of the cumulative welfare loss due to the shock that occurred in the period t^*. The welfare loss $\ell(t)$ is a measure of the areas shaded in Figure 7 and Figure 8. It is an increasing function of the extent of the deviation from the normal (i.e., without shock) trajectory and the time required for the unit to return to the normal (i.e., without shock) trajectory. Dividing both sides of (21) by $\int_{t^*}^{t} W(X(0), t)dt$, one obtains:

$$\hat{\ell}(t) = \frac{\ell(t)}{\int_{t^*}^{t} W(X(0), t)dt} = 1 - \frac{\int_{t^*}^{t} W(X(1), t)dt}{\int_{t^*}^{t} W(X(0), t)dt} \tag{22}$$

$\hat{\ell}(t)$ is a measure at time t of the cumulative welfare loss due to the shock that occurred at the time t^* as a proportion of the cumulative welfare that could be obtained if the shock did not occur. By construction, $\hat{\ell}(t) \in [0,1]$. If $\hat{\ell}(t)$ is close to 0 (1), the loss of welfare due to the shock is small (large), relative to the level of welfare in the absence of the shock. A conceptual measure of resilience is therefore defined as:

$$\mathcal{R}(H) = 1 - \lim_{t \to t^* + H} \hat{\ell}(t) = 1 - \hat{\ell}(t^* + H) \tag{23}$$

where H is a horizon considered large enough to investigate the resilience of the economic unit to the shock. $\mathcal{R}(H) \in [0,1]$ since $\hat{\ell}(t) \in [0,1]$. Also, the larger (smaller) $\mathcal{R}(H)$, the smaller (larger) the welfare loss $\hat{\ell}(t^* + H)$, the more (less) resilient the unit is. Combining (22) and (23), one obtains:

$$1 - \hat{\ell}(t) = \frac{\int_{t^*}^{t} W(X(1), t)dt}{\int_{t^*}^{t} W(X(0), t)dt} \tag{24}$$

$$\int_{t^*}^{t} W(X(1), t)dt = \left[1 - \hat{\ell}(t)\right] \int_{t^*}^{t} W(X(0), t)dt \tag{25}$$

$$\lim_{t \to t^* + H} \int_{t^*}^{t} W(X(1), t)dt = \lim_{t \to t^* + H} \left[1 - \hat{\ell}(t)\right] \times \lim_{t \to t^* + H} \int_{t^*}^{t} W(X(0), t)dt \tag{26}$$

$$\int_{t^*}^{t^*+H} W(X(1),t)dt = \mathcal{R}(H) \times \int_{t^*}^{t^*+H} W(X(0),t)dt \tag{27}$$

$$RCW(H) = \mathcal{R}(H) \times NCW(H) \tag{28}$$

where $RCW(H) = \int_{t^*}^{t^*+H} W(X(1),t)dt$ is the realized cumulative welfare, and $NCW(H) = \int_{t^*}^{t^*+H} W(X(0),t)dt$ is the Normal Cumulated Welfare. Minimizing the impact of the shock amounts to minimizing the distance between RCW and NCW, which means maximizing $\mathcal{R}(H)$. Consequently, maximizing the welfare of an economic unit exposed to shocks is best achieved by developing its resilience capacities. Considering that the total value added is an appropriate measure of the welfare at the country level, the discussion in this section suggests that resilience factors contribute to economic growth by minimizing short- and long-term value-added losses in the economy.

3.3.3. Decomposition of TFP into technical change, technical efficiency, scale efficiency, and allocative efficiency

The production function is represented using a single-output stochastic production frontier model:

$$Y_{it} = f(X_{it}, T, \beta)\exp(-u_{it}) \tag{29}$$

where Y, X, T are defined as in section 3.4.1. i represents the country and t the time period. β is a vector of parameters. u measures the extent of technical inefficiency and is a non-negative random variable following a half-normal distribution. The term $\exp(-u_{it})$ represents the technical efficiency of the country i in period t. Taking the logarithm of both sides of (29) and differentiating the result with respect to T, one obtains:

$$\dot{Y} = \frac{\partial lnf(X,T,\beta)}{\partial T} + \sum_j \epsilon_j \dot{X}_j - \frac{\partial u}{\partial T} \tag{30}$$

where $\epsilon_j = \frac{\partial lnf(X,t,\beta)}{\partial lnX_j}$ is the elasticity of the output with respect to the input j. $\dot{Y}$ and $\dot{X}_j$ are the growth rates of the output and the input j, respectively.

Recall that the rate of growth of the total factor productivity can be expressed as:

$$T\dot{F}P = \dot{Y} - \sum_j S_j \dot{X}_j \tag{31}$$

where $S_j = \frac{W_i X_j}{C}$. Substituting (30) into (31) and rearranging the terms, one obtains:

$$T\dot{F}P = \frac{\partial lnf(X,T,\beta)}{\partial t} - \frac{\partial u}{\partial t} + (\epsilon - 1)\sum_j \dot{X}_j \psi_j + \sum_j (\psi_j - S_j)\dot{X}_j \tag{32}$$

where $\epsilon = \sum_j \epsilon_j$ is the measurement of returns to scale, and $\psi_j = \epsilon_j / \epsilon$. The first term in equation (32) represents technical change:

$$TC = \frac{\partial lnf(X,T,\beta)}{\partial t} \tag{33}$$

Its positive value indicates technical progress (i.e., improvements in best practices). The second term of (32) represents the rate of technical efficiency change:

$$TEC = -\frac{\partial u}{\partial t}, \tag{34}$$

which represents the extent to which the current production practices move closer or farther away from the best practices. The third term of (32) represents the scale change:

$$SC = (\epsilon - 1)\sum_j S_j \dot{X}_j \tag{35}$$

It captures the movements towards or away from the optimal scale of production. The last term of (32) represents the allocative efficiency change:

$$AEC = \sum_j (\psi_j - S_j)\dot{X}_j \tag{36}$$

AEC measures the inefficiency in resources allocation resulting from deviations of input prices from the value of their marginal product (S. Kim & Han, 2001). Thus, the growth of the TFP can be decomposed into technical change, technical efficiency change, scale change, and allocative efficiency change (Kumbhakar & Lovell, 2000):

$$\dot{TFP} = TC + TEC + SC + AEC \tag{37}$$

When there is constant return to scale, $SC = 0$ and $AEC = 0$ since $\psi_j = S_j$ and $\epsilon = 1$. In that case, the rate of growth of TFP can be decomposed as:

$$\dot{TFP} = TC + TEC \tag{38}$$

3.4. Empirical model

3.4.1. Measuring partial factor productivity and total factor productivity using the growth accounting framework

First, it is important to establish the link between partial factor productivity measures and total factor productivity. Following Adelaja (1992b) and Kim (1992), consider the following single-output production function:

$$Y = F(\boldsymbol{X}, T) \tag{39}$$

where Y is the quantity of the output, $\boldsymbol{X}$ is a vector of inputs whose elements are $X_i (i = 1, \dots, n)$, and T is a trend variable that proxies technological change. The production function is assumed to satisfy the usual regularity conditions. Among other properties, I assume that it is continuous, twice differentiable, homogenous, and exhibits constant return to scale.

Assume that the firm operates in competitive markets, let P be the output price, $\boldsymbol{W}$ a vector of input prices whose elements are W_i $(i = 1, \dots, n)$. The maximization of the revenues subject to an expenditure constraint yields the following first-order conditions (FOCs), $\forall i = 1, \dots, n$:

$$P \frac{\partial Y}{\partial X_i} = \lambda W_i \tag{40}$$

$$\sum_{i=1}^{n} W_i X_i = C \tag{41}$$

where λ is the Lagrange multiplier, and C is the total expenditure on inputs. Multiplying both sides of equation (40) by X_i, summing over the is to satisfy the expenditure constraint (41), and rearranging the terms, we get the following expression for the Lagrange multiplier:

$$\lambda = \frac{P \sum_{i=1}^{n} X_i \frac{\partial Y}{\partial X_i}}{C} \tag{42}$$

Using (42), one can rewrite (40) as:

$$\frac{W_i}{C} = \frac{\frac{\partial Y}{\partial X_i}}{\sum_{i=1}^{n} X_i \frac{\partial Y}{\partial X_i}} \tag{43}$$

The equation (43) represents a set of inverse input demand functions. They represent the producer's willingness to pay to acquire a given quantity of the input i given a predetermined level of expenditure (H. Y. Kim, 1992). One can rewrite (43) in terms of cost shares as follows:

$$S_i = \frac{\frac{\partial lnY}{\partial lnX_i}}{\sum_{i=1}^{n} \frac{\partial lnY}{\partial lnX_i}} \tag{44}$$

where $S_i = \frac{W_i X_i}{C}$ is the cost share of the input i and $\sum_{i=1}^{n} S_i = 1$.

Assume that the production function (39) is approximated by the translog form (Christensen et al., 1973):

$$\ln \mathrm{Y} = \alpha_0 + \sum_{i=1}^{n} \alpha_i lnX_i + \delta_T T + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} lnX_i lnX_j + \sum_{i=1}^{n} \gamma_{iT} lnX_i T + \frac{1}{2}\delta_{TT} T^2 \tag{45}$$

where $\beta_{ij} = \beta_{ji}$ $(i \neq j)$. Using (45), one can write the numerator of (44) as:

$$\alpha_i + \sum_{j=1}^{n} \beta_{ij} lnX_j + \gamma_{iT} T \quad (46)$$

The application of Euler's theorem yields:

$$\sum_{i=1}^{n} \frac{\partial lnY}{\partial lnX_i} = 1. \quad (47)$$

Using (46) and (47), one can rewrite equation (44) as:

$$S_i = \alpha_i + \sum_{j=1}^{n} \beta_{ij} lnX_j + \gamma_{iT} T \quad (48)$$

Using equations (45), one can derive the growth of the total factor productivity as:

$$GTFP = \frac{\partial lnY}{\partial T} = \delta_T + \sum_{i=1}^{n} \gamma_{iT} lnX_i + \delta_{TT} T \quad (49)$$

Following Jorgenson (1987) and Adelaja (1992b), the $GTFP$ from the period $t-1$ to t can be proxied with:

$$GTFP_t^* = \frac{1}{2}(GTFP_t + GTFP_{t-1}) \quad (50)$$

Similarly, the average factor shares between the periods $t-1$ and t are proxied with:

$$S_{it}^* = \frac{1}{2}(S_{it} + S_{it-1}) \quad (51)$$

where $\sum_{i=1}^{n} S_{it}^* = 1$. Following the growth accounting framework (Adelaja, 1992a, 1992b; Solow, 1957), the growth of the output between two consecutive periods is:

$$[lnQ_t - lnQ_{t-1}] = GTFP_t^* + \sum_{i=1}^{n} S_{it}^* (lnX_{it} - lnX_{it-1}) \quad (52)$$

Therefore, the growth of the total factor productivity is:

$$GTFP_t^* = [lnQ_t - lnQ_{t-1}] - \sum_{i=1}^{n} S_{it}^* (lnX_{it} - lnX_{it-1}) \quad (53)$$

The growth of the productivity of the input i between two successive time periods is:

$$GFP_{it}^{*} = [lnQ_t - lnQ_{t-1}] - [lnX_{it} - lnX_{it-1}] \quad (54)$$

Substituting (52) into (54), we derive the growth of the productivity of input n as:

$$GFP_{nt}^{*} = GTFP_t^{*} + \sum_{i=1}^{n-1} S_{it}^{*} \{(lnX_{it} - lnX_{it-1}) - (lnX_{nt} - lnX_{nt-1})\} \quad (55)$$

By construction, the measures of the growth rates of factors' productivity computed using (55) and total factor productivity growth rates using (53) are consistent with the translog approximation of the production function (45).

One can also decompose total factor productivity growth in terms of factors' productivities. Following Adelaja (1992b), one may express (53) as:

$$GTFP_t^{*} = \sum_{i=1}^{n} S_{it}^{*} (lnQ_t - lnQ_{t-1}) - \sum_{i=1}^{n} S_{it}^{*} (lnX_{it} - lnX_{it-1}) \quad (56)$$

$$GTFP_t^{*} = \sum_{i=1}^{n} S_{it}^{*} \{(lnQ_t - lnQ_{t-1}) - (lnX_{it} - lnX_{it-1})\} \quad (57)$$

$$GTFP_t^{*} = \sum_{i=1}^{n} S_{it}^{*} GFP_{it}^{*} \quad (58)$$

Equation (58) is obtained by substituting (54) into (56). It shows that total factor productivity growth is a weighted average of the growth rates of partial factor productivities, where the weights are the cost shares. Equation (58) indicates that, in the short term, if a shock affects at least one partial factor productivity, it is likely to affect the total factor productivity. Furthermore, assuming that the cost shares are fixed, which is likely in the short-run, Equation (58) shows that a shock that negatively affects the growth rate of the productivity of an input k (or a set of inputs K) will result in a negative change in the total factor productivity growth rates only if this negative effect is not sufficiently offset by a simultaneous change in the productivity of another input l (or a set of other inputs $L, L \neq K$). If so, the ability of the economic agent to proceed with this offsetting mechanism is a form of absorptive resilience capacity because it enables the economic agent to absorb the effect of the shock on the short-term trajectory of total factor productivity. The long-run effects depend on both the long-run effects of the shock on partial factor productivities and the changes in the input mix that will modify the cost shares.

3.4.2. Estimating the impact of shocks on productivity measures

Next examine the impact of shocks on the growth of partial productivity measures (PF) and total factor productivity (TFP). Various specifications were used in the literature to investigate the determinants of partial productivity or total factor productivity measures, including shocks (for instance, see Adelaja (1992b), Lukongo and Rezek (2018), Appau et al. (2021); Liu et al. (2020)). A geometric (or Koyck) distributed lag model is used to study the short- and long-term effects of the shocks on the productivity measures.

Assuming an infinite distributed lag for each explanatory variable, the model is specified as:

$$y_{it} = \alpha^* + \gamma C_{it} + \sum_j \gamma_j^* X_{jit} + \rho y_{i,t-1} + a_i + b_t + u_{it}^* \qquad (59)$$

where y denotes a productivity measure, C is a measure of the shock, X is a vector of control variables, a_i represents the unobserved effects, and b_t the time fixed effects. The measure of conflicts is the number of fatalities per 100 persons. The measures of droughts include the number of deaths per 100,000 persons and the number of droughts events recorded per 100,000 persons. Selecting control variables that enter a geometric (Koyck) distributed lag model entails a trade-off between the relevance of variable, efficiency gains on the coefficients of interest, and the likelihood of the infinite distributed lag imposed on the variable by the Koyck model. As a result, the control variables selected include the total value of imports and exports as a percentage of the GDP and the net inflows of foreign direct investments as percentage of GDP.

γ_j^* captures the instantaneous impact of the variable X_j. γ captures the instantaneous impact of the shock. Assuming a permanent change in the level of the shock's indicator, the cumulative effect of the shock after n periods is $IMPn = \frac{\gamma(1-\rho^{n+1})}{1-\rho}$. Under the same assumption, the long-run impact (referred to as Long Run Propensity) of the shock is given by $LRP = \frac{\gamma}{1-\rho}$. The stability condition of the Koyck model is $|\rho| < 1$. I report the values of $IMPn, for\ n = 0\ to\ 5$ and LRP along with their statistical significance. Note that $IMP0 = \gamma$. The conceptual measures of resilience defined in section 3.3.2 are proxied as follows: the greater the number of time periods in which $IMPn$ is negative and statistically significant, the larger the value of $\hat{\ell}(n)$ which is the cumulative loss in welfare due to the shock as measured n periods after the shock, and the smaller the value of $\mathcal{R}(n)$ which represents the degree of resilience as measured n periods after the shock. A negative and statistically significant sign of the LRP suggests that $\hat{\ell}(\infty)$ is very large (i.e., very large the cumulative loss in welfare over the long run) and $\mathcal{R}(\infty)$ is very small (i.e., very small degree of resilience as measured several years after onset of the shock).

By construction, $y_{i,t-1}$ is endogenous in (59). This issue is addressed by estimating (59) using $\mathrm{C}_{\mathrm{i,t-1}}$, $\mathrm{X}_{\mathrm{i,t-1}}$ as instruments for $y_{i,t-1}$. As explained by Wooldridge (2013) in a time series setup, provided strict exogeneity assumption, these instruments satisfy the relevance and exogeneity criteria. I also cluster the standard errors at the country level. Additional estimations that attempt to address the endogeneity issue using the Arellano–Bond (1991) estimator (hereafter referred to as GMM) and the system GMM (hereafter referred to as SYS-GMM) estimator, proposed by Blundell and Bond (1998) were also attempted. GMM and SYS-GMM are not the preferred estimators because they require no autocorrelation in the idiosyncratic errors. Their related results are available upon request.

3.4.3. Estimating the impact of shocks on technical and scale efficiencies

To estimate the impact of shocks on technical efficiency (TE) and scale efficiency (SE), I first use input-oriented Data Envelopment Analysis (DEA) models to compute the yearly levels of TE and SE assuming constant returns to scale (CRS) using the approach introduced by Charnes et al. (1978) or variable return to scale (VRS) using the approach introduced by Färe et al. (1983) and Banker et al. (1984). The DEA models are based on non-parametric construction of the frontier based on linear programming (LP) and are widely utilized in the productivity and efficiency literature (Coelli et al., 2005).

As in previous sections, let c denote the county, P the number of countries, t the year, and T the number of years. At time t, q_{ct} is the output of country c, $\boldsymbol{x_{ct}}$ the $1 \times N$ vector of inputs used by c, $\boldsymbol{Q}_t$ the $1 \times P$ output vector, and $\boldsymbol{X}_t$ the $N \times P$ input matrix.

Assuming CRS, the level of technical efficiency of country c at time t is computed by solving the following LP problem:

$$\begin{aligned} &\min_{\theta,\lambda} \theta \\ &\text{s.t.,} \quad -q_{ct} + \boldsymbol{Q}_t\boldsymbol{\lambda} \geq \boldsymbol{0} \\ &\qquad\quad \theta\boldsymbol{x_{ct}} - \boldsymbol{X}_t\boldsymbol{\lambda} \geq \boldsymbol{0} \\ &\qquad\quad \boldsymbol{\lambda} \geq \boldsymbol{0} \end{aligned} \tag{60}$$

where θ is a scalar and $\boldsymbol{\lambda}$ is a $P \times 1$ vector of constants. The value of θ is the efficiency score of country c in year t assuming CRS, which I denote as $TECRS_{ct} = \theta$. $\theta \leq 1$ and a value of 1 indicates that country c is technically efficient according to Farrell's (1957) definition. Accounting for VRS entails adding the convexity constraint $\boldsymbol{I}'\boldsymbol{\lambda} \geq \boldsymbol{0}$ to the LP problem (60), where $\boldsymbol{I}$ is a vector of ones:

$$\min_{\theta,\lambda} \theta$$

$$\text{s.t.,} \quad -q_{ct} + \boldsymbol{Q}_t\boldsymbol{\lambda} \geq \boldsymbol{0}$$

$$\theta\boldsymbol{x_{ct}} - \boldsymbol{X}_t\boldsymbol{\lambda} \geq \boldsymbol{0}$$

$$\boldsymbol{I}'\boldsymbol{\lambda} \geq \boldsymbol{0}$$

$$\boldsymbol{\lambda} \geq \boldsymbol{0} \quad (61)$$

In this case, the value of θ is the efficiency score of country c in year t assuming VRS, which I denote as $TEVRS_{ct} = \theta$. Let T denote the number of years. Solving each LP problem (60) and (61) $P \times T$ times yields the values of $TECRS$ and $TEVRS$ per country and year.

While the CRS assumption fits well with firms operating at an optimal scale, market failures (imperfect competition, government interventions, financial constraints, etc.) may cause economic units to not operate at the optimal scale (Coelli et al., 2005). These failures exist in the sub-Saharan African context, which is the focus of this study. In such situations, it is preferable to relax the CRS assumption by relying on VRS (Afriat, 1972; Banker et al., 1984; Coelli et al., 2005; Färe et al., 1983). Computing both TECRS and TEVRS enables us to compute the Scale Efficiencies (SE)[4] since

$$SE = \frac{TECRS}{TEVRS} \quad (62)$$

Next, I regress the measures of $TECRS$, $TEVRS$, and SE on our indicators of shocks using pooled Tobit and the Correlated Random Effect Tobit (CRE Tobit) regression proposed by Wooldridge (2002). The Tobit models are used because $TECRS$ and $TEVRS$ are corner solution outcomes, taking the value 1 for several observations.

3.4.4. Data

[4] Several authors like Coelli et al. (2005) provide the detail of the derivation of this formula

The latest dataset made publicly available by the U.S. Department of Agriculture and Economic Research Service (2021) on international agricultural total factor productivity are used to compute the growth rated of partial productivities and total factor productivity. The output is measured as the gross value of agricultural output from crops, livestock and aquaculture, expressed in $1,000 at constant 2015 prices. The inputs include land, labor, machinery, livestock, fertilizer, and feed. Land is represented by the quality-adjusted agricultural area expressed in 1,000 hectares of "rainfed-equivalent cropland". Labor is represented by the number of economically active adults primarily employed in agriculture, expressed in 1,000 persons. Machinery is represented by the inventories of farm machinery, measured in thousands of metric horsepower (1,000 CV) in tractors, combine-threshers, and milking machines. Livestock is represented by the farm inventories of livestock and poultry, measured in 1,000s of Standard Livestock Units. Fertilizer is measured by the total N, P2O5, K2O nutrients from inorganic fertilizers and N from organic fertilizers applied to soils, in 1,000 metric tons. Feed is represented by the total energy content of feeds measured in thousands of mega-calories (Mcal). For detailed explanations of these measures the reader is referred to (Fuglie, 2015). The ERS-USDA provides data on these measures of input and outputs over the period 1961-2019. Due to data limitations, I borrow the time-invariant cost shares from Fuglie (2015), which are also used by the ERS-USDA. These cost shares are presented in Table 6.

The number of fatalities per 100 persons is computed based on the number of fatalities provided by the publicly available data provided by the Armed Conflict Location and Event Data (ACLED) (Raleigh et al., 2010). The number of deaths per 100,000 persons due to droughts is computed based on the publicly Emergency Events Database EM-DAT (CRED, n.d.). The data on total population, the value of trade as percentage of GDP, and the net inflows of foreign direct investments as percentage of GDP are drawn from the World Development Indicators (WDI) published by the World Bank. Given the availability of data on these various indicators, our sample includes 41 sub-Saharan African countries and covers the 23 years period 1997-2019. Table 7 presents the descriptive statistics.

Table 6: Input cost shares

Input	Cost share
Labor	0.248
Land	0.315
Livestock	0.308
Machinery	0.024
Fertilizer	0.055
Feed	0.049

Source: Adapted from Fuglie (2015)

Table 7: Descriptive statistics

Variable	Unit	Obs.	Mean	Std. Dev.	Min	Max
Output	$1,000 constant 2015	989	4,974,330	7,917,426	51,913	59,306,332
Land	1,000 ha	989	5,401	8,238	36	62,460
Labor	1,000 persons	989	4,091	5,619	35	34,605
Machinery	1,000 CV	989	258	571	0	4,246
Livestock	1,000s of SLU	989	8,096	12,352	13	70,624
Fertilizer	1,000 metric tons	989	87,326	159,023	123	928,385
Feed	1,000 Mcal	989	3,308,724	8,236,705	2,160	60,118,544
Conflicts fatalities	Number	989	640.39	3,545.84	0.00	73,811.00
Drought deaths	Number	989	21.36	636.17	0.00	20,000.00
Drought events	Number	989	0.15	0.36	0.00	2.00
Trade openness	Number	963	54.01	31.02	7.81	244.89
FDI	%	962	4.28	8.22	-11.20	103.34

3.5. Results

3.5.1. Growth rates of productivity measures

Table 8: Growth rates of productivity measures

Variable	Obs.	Mean	Std. Dev.	Min	Max
TFP Growth	924	.008	.072	-.373	.319
Productivity growth of:					
Land	924	.013	.093	-.789	.803
Labor	924	.013	.09	-.427	.406
Livestock	924	.006	.094	-.634	.383
Machinery	924	.018	.101	-.429	1.013
Fertilizer	924	-.01	.275	-2.059	1.621
Feed	924	-.012	.181	-1.034	1.113

Table 8 reports the average growth rates of computed productivity measures over the countries and period studied. On average, the TFP increased at a rate of 0.8 percent per year, suggesting that there were as many good and bad performances in terms of country level agricultural TFP growth. The growth of the agricultural TFP was accompanied through growth in the productivities of land, labor, livestock, and machinery, while the negative growth rates of the productivities of fertilizer and feed slowed it down. These results suggest that, at the regional scale, the structure of the agricultural production is improving slowly, mainly driven by improvements in the quality and the quality of the use of land, labor, livestock, and machinery, and the quality of their use. However, there are negative trends in the quality of fertilizers and feeds and the quality of their use.

3.5.2. Impact of conflicts on the structure of agricultural production

As shown in Table 9 (column 1), in the short-run, conflicts negatively impact on the growth rate of agricultural TFP. This finding means that not only does the onset of a conflict cause the TFP to instantaneously deviate from its normal path, but the higher the intensity of the conflict, the more the TFP is derailed (i.e., Δ in section 3.2.2 is larger). More precisely, conflicts negatively affect TFP by reducing the productivity of livestock, machinery, and fertilizer (see Table 9, models 4, 5, and 6). In other words, conflicts instantaneously disrupt the structure of agricultural transformation through instantaneous declines in the quality and quality of use of livestock, machinery, and fertilizer. The adverse effect on livestock's productivity may reflect the reduced access to good pastures in or near conflict-prone areas. Having recourse to poorer pastures reduce the productivity of the livestock. The instantaneous drop in machinery's productivity may indicate the disruption of machinery rental markets and the reduced accessibility to complementary services or inputs (credit, reparation services, tractors drivers, etc.). In the case of Boko Haram, evidence suggest that they particularly target machinery and equipment for destruction (Kergna et al., 2014). The instantaneous drop in fertilizers' productivity reflects the reduced access to good quality of fertilizers due to their lower supply and more difficult access to materials' markets.

The null hypotheses that conflicts do not have persistent effects over time on the growth of agricultural TFP is not rejected. This is consistent with the long-run trend in agricultural growth over time and with the result that countries use to bounce back to pre-conflict levels of economic growth (Adelaja & George, 2019a). Thus, the overall structure of the production is only instantaneously disrupted by a conflict, suggesting a high degree of resilience (i.e., $\hat{\ell}(n)$ is small meaning that the cumulative loss in welfare due to the conflicts is small and $\mathcal{R}(n)$ is high meaning that the path of TFP quickly returns to the without conflict path). However, the significant adverse effects of conflicts on machineries and fertilizers' productivities persist several periods and over the long run (see Table 9, columns 5 and 6). In these cases, $\hat{\ell}(n)$ is large and $\mathcal{R}(n)$ is small. This is consistent with the fixed nature of machinery and equipment as capital assets. Therefore, even though the overall productivity of the sector bounces back to its normal path over time, the structure of production permanently changes toward greater reliance on poorer quality machinery and fertilizer, and lower levels of use. These persistent effects suggest that the adverse effects of conflicts on the environment of the agricultural production remain several years after the conflict. For instance, if actors involved in the machinery rental markets or maintenance leave the areas prone to conflicts and do not return after the conflict, the effects of the conflicts will remain well after the conflicts end, and in this case, that will be reflected in the fall of machineries' productivity in the long run. Hence, conflicts do not permanently disrupt the path of TFP but they significantly affect the transformation of the agricultural production by inducing long-term disruptions in the improvements in machineries and fertilizers use and quality.

When it comes to the effect on technical efficiency, the estimates (reported in appendix A2, tables 39 to 44) suggest that conflicts might decrease the level of technical efficiency. Indeed, the pooled Tobit regression yields a negative and statistically significant impact of conflicts on the level of technical efficiency. However, the statistical significance is not sustained when using the CRE Tobit model.

Table 9: Impact of conflicts on productivity measures

	TFP growth rate	Inputs' productivity growth rate					
		Land	***Labor***	***Livestock***	***Machinery***	***Fertilizer***	***Feed***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fatalities per 100 persons	-0.0945**	-0.0247	-0.0726	-0.133**	-0.0292**	-0.219***	-0.0697
	(0.0390)	(0.0273)	(0.130)	(0.0616)	(0.0118)	(0.0398)	(0.0542)
Lags of inputs' productivity growth rate							
TFP	0.381						
	(0.379)						
Land		-0.0178					
		(0.451)					
Labor			0.136				
			(0.847)				
Livestock				0.655			
				(0.543)			
Machinery					-0.308		
					(0.494)		
Fertilizer						0.0876	
						(0.242)	
Feed							0.0477
							(0.530)
Share of trade in GDP	-8.40e-05	0.000101	-4.21e-05	-4.56e-05	7.73e-05	-0.00109*	-0.000725
	(0.000132)	(0.000193)	(0.000201)	(0.000179)	(0.000419)	(0.000624)	(0.000809)
Share of FDI in GDP	0.000160	0.000301	0.000128	1.84e-05	-0.000106	0.000713	0.000792
	(0.000152)	(0.000256)	(0.000346)	(0.000275)	(0.000521)	(0.000552)	(0.00137)
Observations	851	851	851	851	851	851	851
Number of id	41	41	41	41	41	41	41
IMP0	-.094**	-.025	-.073	-.133**	-.029**	-.219***	-.07
IMP1	-.13	-.024	-.082	-.221	-.02	-.239***	-.073
IMP2	-.144	-.024	-.084	-.278	-.023**	-.24**	-.073
IMP3	-.149	-.024	-.084	-.315	-.022	-.24**	-.073
IMP4	-.151	-.024	-.084	-.34	-.022*	-.24**	-.073
IMP5	-.152	-.024	-.084	-.356	-.022*	-.24**	-.073
LRP	-.153	-.024	-.084	-.386	-.022*	-.24**	-.073

Notes: Each column refers to a separate regression. The dependent variable is mentioned in the first row. Estimations by FE-2SLS where the lag of the dependent variable is endogenous. Instruments include the lag of the shock variable and lags of control variables. All regressions include a constant term and time fixed-effects. Standard errors robust to intra-country correlation of observations are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.5.3. Impact of droughts on the structure of agricultural production

Table 10 reports the effects of droughts intensity measured using the number of deaths due to droughts per 100,000 persons on productivity measures. One may consider this indicator to reflect severe droughts because the latter led to people's death. The results show that a higher intensity of drought leads to instantaneous and persistent declines or slowdown in the productivity of land, labor, livestock, machineries, and fertilizers. Also, these lead to instantaneous and permanent declines in agricultural TFP. In these cases, the associated measures of $\hat{\ell}(n)$ are large and $\mathcal{R}(n)$ are small, meaning that severe droughts cause high losses in welfare and slow bouncing back to the without drought path of productivity growth. Thus, not only do severe droughts permanently reduced the overall productivity, they also permanently disrupt the structure of the agricultural production. The latter effect occur through permanent drops in the quality and the quality of use of land, labor, livestock, machinery, and fertilizer.

An example of the short-term effects of a shock on land productivity may include the adverse effect of an instantaneous fall in water availability while an expel of a long-term effect may include the result of forced displacements or an indication of the long-term alteration of climatic conditions. The long-term fall in labor productivity as a result of a shock may accrue through the non-return of good quality workers who permanently leave an area when the shock occurs. A long-term decline in livestock productivity may result from herders' forced displacement which force them to move from places where good quality pastures are available to places where the quality is poorer. Since climate change is accompanied in some places by higher intensity of drought events, the long-term effects of droughts on livestock productivity may accrue through the decline in the productivity of pasture soils. The long-term fall in machinery productivity may result from the displacement of qualified workers who provide maintenance services or maintain machines rental markets. The fall in fertilizers productivity may result from the long-term deterioration of climate conditions, which degrade soil quality.

By providing estimates based on the number of droughts events per 100,000 persons as a measure of droughts, Table 11 allows one to explore if the results differ for less severe droughts. Table 5.4 shows that only labor and livestock productivities are adversely affected by droughts, and only labor productivity is permanently affected. Consequently, droughts certainly affect the quality of labor available and the management of human resources, on the short-and long run. As the severity of the drought increases, the structure of the production is increasingly hurt because more inputs are significantly affected and this process leads to a permanent decline or slowdown of the agricultural TFP. The results presented in the appendices suggest that both indicators of droughts do not have any statistically significant effect on the level of technical efficiency.

Table 10: Impact of droughts deaths on productivity measures

	TFP growth rate	Inputs' productivity growth rate					
		Land	***Labor***	***Livestock***	***Machinery***	***Fertilizer***	***Feed***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Droughts deaths per 100,000 persons	-0.0489***	-0.0384***	-0.0507***	-0.0297**	-0.0518***	-0.306***	0.0821*
	(0.00891)	(0.00647)	(0.0120)	(0.0130)	(0.0111)	(0.0233)	(0.0439)
Lags of inputs' productivity growth rate							
TFP	-0.346*						
	(0.209)						
Land		-0.0717					
		(0.277)					
Labor			-0.498*				
			(0.282)				
Livestock				-0.659**			
				(0.278)			
Machinery					-0.198		
					(0.215)		
Fertilizer						-0.00111	
						(0.121)	
Feed							-0.211
							(0.365)
Share of trade in GDP	-7.62e-05	7.69e-05	3.86e-06	9.97e-05	1.19e-05	-0.00131**	-0.000942
	(0.000167)	(0.000182)	(0.000229)	(0.000251)	(0.000393)	(0.000614)	(0.000905)
Share of FDI in GDP	0.000223	0.000306	0.000381	-6.25e-05	-0.000165	0.000588	0.000432
	(0.000187)	(0.000221)	(0.000390)	(0.000324)	(0.000407)	(0.000533)	(0.00125)
Observations	851	851	851	851	851	851	851
Number of id	41	41	41	41	41	41	41
IMP0	-.049***	-.038***	-.051***	-.03**	-.052***	-.306***	.082*
IMP1	-.032***	-.036***	-.025	-.01	-.042**	-.306***	.065
IMP2	-.038***	-.036***	-.038***	-.023***	-.044***	-.306***	.068
IMP3	-.036***	-.036***	-.032**	-.015	-.043***	-.306***	.068
IMP4	-.036***	-.036***	-.035***	-.02**	-.043***	-.306***	.068
IMP5	-.036***	-.036***	-.033**	-.016	-.043***	-.306***	.068
LRP	-.036***	-.036***	-.034***	-.018*	-.043***	-.306***	.068

Notes: Each column refers to a separate regression. The dependent variable is mentioned in the first row. Estimations by FE-2SLS where the lag of the dependent variable is endogenous. Instruments include the lag of the shock variable and lags of control variables. All regressions include a constant term and time fixed-effects. Standard errors robust to intra-country correlation of observations are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Impact of droughts events on productivity measures

	TFP growth rate	Inputs' productivity growth rate					
		Land	***Labor***	***Livestock***	***Machinery***	***Fertilizer***	***Feed***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Droughts events per 100,000 persons	-0.169	1.236	-0.927**	-0.615*	0.362	0.0229	-0.336
	(0.404)	(0.878)	(0.379)	(0.331)	(1.235)	(1.191)	(0.862)
Lags of inputs' productivity growth rate							
TFP	-0.939						
	(0.833)						
Land		-0.532**					
		(0.217)					
Labor			-0.727**				
			(0.292)				
Livestock				-0.260			
				(0.306)			
Machinery					-0.0265		
					(0.457)		
Fertilizer						-0.0160	
						(0.319)	
Feed							-0.550
							(0.860)
Share of trade in GDP	1.47e-05	0.000102	9.54e-05	6.42e-05	-2.11e-05	-0.00118*	-0.00125
	(0.000250)	(0.000237)	(0.000246)	(0.000228)	(0.000310)	(0.000634)	(0.00141)
Share of FDI in GDP	0.000317	0.000459	0.000478	-7.20e-05	-0.000241	0.000548	4.49e-05
	(0.000352)	(0.000343)	(0.000463)	(0.000283)	(0.000453)	(0.000525)	(0.00196)
Observations	851	851	851	851	851	851	851
Number of id	41	41	41	41	41	41	41
IMP0	-.169	1.236	-.927**	-.615*	.362	.023	-.336
IMP1	-.01	.578	-.253	-.455	.352	.023	-.151
IMP2	-.159	.928	-.743**	-.496	.352	.023	-.253
IMP3	-.019	.742	-.387	-.486	.352	.023	-.197
IMP4	-.151	.841	-.646**	-.488	.352	.023	-.228
IMP5	-.027	.788	-.458	-.488	.352	.023	-.211
LRP	-.087	.807	-.537**	-.488	.352	.023	-.217

Notes: Each column refers to a separate regression. The dependent variable is mentioned in the first row. Estimations by FE-2SLS where the lag of the dependent variable is endogenous. Instruments include the lag of the shock variable and lags of control variables. All regressions include a constant term and time fixed-effects. Standard errors robust to intra-country correlation of observations are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.6. Conclusion and policy implications

Agricultural and economic growth in sub-Saharan African (SSA) countries are exposed to several natural and artificial events that threaten the processes of agricultural growth and economic transformation. Indeed, these issues have dominated the policy debates in SSA since those countries' independence. While micro- and macro- drivers of agricultural and economic transformations were thoroughly examined in the development literature, the under-consideration of the disruptive role conflict and climate-related shocks and stressors on the transformation processes is alarming, especially given their growing intensity and frequency in recent years.

Productivity measures have been shown to be appropriate for tracking agricultural and economic transformations. However, previous studies that examined the effects of shocks on productivity at either the micro or macro scales have been limited by their limited consideration of long-term dynamics. Therefore, they do not provide evidence on how these shocks affect these transformations. The results of this study suggest the existence of disruptive short- and long-term effects of droughts and conflicts on agricultural productivity and thus on the process of agricultural transformation. They also explain the channels through which these disruptions occur, thanks to a comprehensive examination of the effects on almost all the main inputs entering agricultural production. To sum up, the results indicate that conflicts do not permanently disrupt the path of TFP, but they significantly affect the transformation of agricultural production by inducing long-term disruptions in the improvements in machinery and fertilizers' use and quality. However, droughts persistently disrupt the use and quality of land, labor, livestock, machinery, and fertilizer and thus the structure of agricultural production.

The examination of the persistence of these effects enables this study to provide a perspective on resilience that is complementary to the previous resilience measurement approaches based on measurements and analysis of resilience factors. The results show how the variability in the degree of resilience to each shock and across inputs translates into different degrees of resilience of the agricultural total factor productivity. Overall, they suggest that the structure of agricultural production is more resilient to conflicts than to droughts. Provided the central role of productivity in agricultural and economic transformation, these results stress that building productivity resilience should be the at the core of development strategies. For instance, investing in irrigation in drought prone areas can help build productivity resilience, thus limiting the disruptions in the path of agricultural transformation.

From a business or entrepreneurship perspective, the results imply that a shock can have persistent adverse effects on the availability of the package of inputs and services that farmers – or prospective farmers – need to engage and prosper in farming (e.g., permanent displacement of good quality agricultural laborers or qualified workers who provide maintenance services or maintain machines rental markets). Hence, the study also informs the process strategies aiming at improving the business environment of agriculture by showing that building resilience to various forms of shocks also matters.

Further research is needed to build on the result from this study, including micro-scale investigations of the dynamics effects of conflicts, droughts, and other shocks that threaten economic development or transformation in developing regions.

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CHAPTER 4. ESSAY 3: SECTORAL AND SEASONAL LABOR REALLOCATION EFFECTS OF CONFLICTS

4.1. Introduction

In developing economies, given the limited availability of capital, labor and land are key resources which agrarian households seek to optimize to achieve economic viability. Households particularly allocate family labor resources between various economic activities and supplement this with hired labor when available and appropriate. The literature has documented the impact of various shocks and stressors on farm households, as well as the importance of coping strategies used by individuals and households facing various forms of shocks and stressors (Berman et al., 2015; Brück et al., 2019; Debela et al., 2012; Eriksen & Silva, 2009; Gupta et al., 2021; Kansiime et al., 2021; Reardon et al., 1988). A common strategy by farmers is to reallocate labor between specific farm activities and/or between farm and non-farm activities (Branco & Féres, 2021; Cameron & Worswick, 2003; Cunguara et al., 2011; Fernández et al., 2014; Kochar, 1999). For example, increased involvement in non-farm activities was observed among (a) Columbian farmers exposed to conflicts (Fernández et al., 2014); and (b) Mozambican, Ugandan, Kenyan, Brazilian, Indonesian, Indian, and Mexican farmers subject to adverse weather conditions such as droughts, floods, and extreme heat (Branco & Féres, 2021; Cameron & Worswick, 2003; Cunguara et al., 2011; Jessoe et al., 2018; Kijima et al., 2006; Kochar, 1999; Mathenge & Tschirley, 2015; Rose, 2001). Changes in involvement in off-farm activities were also detected in the presence of idiosyncratic shocks in the case of Indonesia (Cameron & Worswick, 2003).

With conflicts and violence on the rise across the globe, with debilitating socioeconomic effects in developing countries (ACLED, 2021; United Nations, 2022; United Nations & World Bank, 2018), the limited evidence on individuals' and households' labor reallocation responses is noteworthy. A rare case study in Colombia found that households respond to violent shocks by substituting off-farm agricultural work for off-farm non-agricultural work (Fernández et al., 2014). Specifically, men responded to violent shocks by reducing their involvement in off-farm agricultural activities and increasing their involvement in off-farm non-agricultural activities. However, women reduced their leisure time and devoted more time to household chores and childcare (Fernández et al., 2014). Other studies investigating how exposure to conflicts affects the time spent in agriculture (e.g., Adelaja and George, 2019a; Odozi and Uwaifo Oyelere, 2021) do not examine the parallel changes in the time allocated to other sectors or activities. Conflicts reportedly impede farm investment, production, and profitability (Arias et al., 2019; Mitchell, 2019), income and poverty (Odozi & Oyelere, 2019), food security (George et al., 2020), resilience capacity (Brück et al., 2019), children health (Akresh et al., 2011, 2012; Ekhator-Mobayode & Abebe Asfaw, 2019; Minoiu & Shemyakina, 2012, 2014; Nwokolo, 2014) and educational outcomes (Akresh & de Walque, 2008; Bertoni et al., 2019; Shemyakina, 2011).

The main objective of this essay is to expand the literature by providing evidence of changes in the choice of types of work (namely, participation in family farm and non-farm enterprises and employment) and sector of employment (namely, employment in in agriculture, manufacturing, and services) as a result of a greater exposure to conflicts. Specifically, Nigeria is used as a case study to investigate how conflicts affect (a) the participation of individuals in family farm enterprises, family non-farm enterprises, and employment with others; and (b) participation and time spent in jobs in the agriculture, manufacturing, and services sectors. In addition, the effects of short- and long-term exposure to conflicts are compared. Furthermore, the effects across seasons, genders, and levels of skill are differentiated. For such purposes, data from the Nigerian General Household Survey (GHS) and the Armed Conflict Location and Event Data (ACLED) Project (Raleigh et al., 2010) are spatially joined to estimate the effects of individuals' exposure to conflicts on the outcomes of interest. The Nigeria GHS provides a range of individual and household level socioeconomic information for a panel of nearly 5,000 households, while ACLED provides information on the location and intensity of conflict events.

The Nigerian experience with conflicts is noteworthy given the availability of data on past and ongoing conflicts and external validity reasons. Peace and security in Nigeria are threatened by violent events perpetrated by armed groups for various motives ranging from religious to separatism claims. These include the Boko Haram Islamist insurgency in the northeast, the conflict between cattle herders and farmers spreading from the central belt southward, the Niger Delta Vigilante, the Indigenous People of Biafra in the southeast, the Shia Islamic Movement of Nigeria in central Nigeria, and Islamic State West Africa Province in the northeast. These violent events create humanitarian crises, displace millions of people, limit the range of available livelihood activities, and ultimately exacerbate poverty and food insecurity (FAO, 2017a; International Crisis Group, 2018; WFP, 2017).

The forms of non-agricultural activities examined in this study differ from those previously studied (e.g., Cunguara et al., 2011; Debela et al., 2012; Jessoe et al., 2018; Kijima et al., 2006). It is argued that grouping activities into agriculture, manufacturing, and services enables one to derive implications for sectoral productivities and structural transformation, even though the latter is a long term process. For instance, due to diminishing marginal productivity of labor, a rise in the number of people entering the agricultural sector as a result of a shock might reduce the labor productivity in this sector. The same rationale applies to manufacturing and services. While agriculture in developing countries is already known for concerning levels of productivity and poverty (see World Bank, 2007), non-agricultural sectors are not untouched. Indeed, a substantial part of the non-agricultural workers experience either time-related underemployment (i.e., they work less than would like to) or invisible underemployment (i.e., they earn less than the minimum wage) (Roubaud & Torelli, 2013). For instances, in the period 2000-2012, the rate of time-related underemployment reached 12.6 percent in Abidjan, 17.1 percent in Bamako, and 16.1 percent in Niamey (Roubaud & Torelli, 2013). The rate of invisible underemployment reached 61.1 percent in Cotonou, 40.8 percent in Kinshasa, and 53.2 percent in Abidjan (Roubaud & Torelli, 2013). These figures suggest that a substantial part of the non-agricultural population is vulnerable to conflicts and violent events, especially since they can directly affect both urban and rural areas. In contrast, shocks such as droughts mainly affect farmers and indirectly affect urban areas. Hence, the limited evidence on how shocks affect household involvement in manufacturing and services in developing countries needs to be addressed. In addition to cross-sectoral changes, the reallocation of labor between activities within the same sector is an additional source of concern. For instance, the shift to lower profitability farm activities observed among Colombian farmers exposed to violent shocks (Arias et al., 2019) can exacerbate poverty and food insecurity.

The second contribution of this study is the comparison of the effects of conflicts between the planting and harvesting seasons. The advantages of exploring seasonal differences include insights into which farm activities are more likely to be affected along the agricultural cycle and which agricultural-related supply chains are more sensitive to conflicts. For instance, greater sensitivity during the planting season may suggest an impact on seeds or fertilizer supply chains. Thus, this analysis has potential implications for the design of better targeted short-term support measures for individuals experiencing such shocks. Another contribution to the strand of the literature examining the disruptive effects of conflicts on resilience (Brück et al., 2019) is the provision of evidence of the effects of conflicts on the diversity of individuals' occupations. This is important since more resilient households can better withstand the effects of conflicts and other idiosyncratic or covariate shocks (Adelaja et al., 2020, 2021; Brück et al., 2019).

Yet another contribution of this study is the comparison of the effects on skilled versus unskilled workers. This has implications for sectoral productivity differences given the widely documented positive effect of human capital on productivity (see Hall and Jones, 1999; Hayami, 1969). The last contribution is of a methodological nature. That is, this study also compares the impacts of conflicts using the two most frequent measurement approaches of conflicts: (1) the approach based on the intensity of conflicts in an administrative division such as the Local Government Area (LGA) (e.g., Adelaja and George, 2019a, 2019b; George et al., 2020; Odozi and Uwaifo Oyelere, 2021), and (2) the approach based on the intensity of conflicts in circular areas (also called "buffer zones") surrounding the observation units (e.g., Bertoni et al., 2019). This comparison enables one to test the presence of the so-called "edge effects" widely documented in the spatial data analysis literature (e.g., Yamada, 2009) and which can limit the quality of the results. Additionally, this study adds to the limited literature which compares the effects of short- and long-term exposure to conflicts (Odozi & Oyelere, 2019; Odozi & Uwaifo Oyelere, 2021).

These contributions are important in the development of strategies to reverse the spread of violent events and improve the resilience of individuals and households' livelihoods to these shocks. Specifically, the findings stress the relatively high vulnerability of agricultural activities (including family enterprises or jobs) as well as the vulnerability of low-skilled individuals. Hence, they pinpoint the importance of improved access to education and the labor market. Additionally, the seasonality effects observed may be useful in improving the targeting of short-term support measures to individuals exposed to violent shocks. The reallocation of efforts across sectors are also important from a productivity perspective because a massive displacement of labor from one sector to another can reduce sectoral productivities and this issue is of major concern for policy makers considering the importance of productivity gains in development strategies.

The rest of the essay is organized as follows. The next section characterizes the allocation of the Nigerian labor force and explains why an important portion of the labor force is vulnerable to shocks. It also presents the spread and rising intensity of conflicts over time in Nigeria. Section 4.3 presents a theoretical model which explains the relationship between conflict exposure and labor allocation choices. Section 4.4 describes the sources of data, measures of conflicts and outcomes of interest, as well as the empirical strategy. Finally, section 4.5 presents and discusses the results, while section 4.6 concludes and derives the policy implications.

4.2. Background

4.2.1. Allocation and vulnerability of the Nigerian labor force

Nigeria is the largest economy and the most populous country in Africa. Over the last decade, its population grew at an average rate of 2.61% per year[5]. As of the last quarter of 2020, the working age and the labor force populations reached 122 and 69 million respectively (NBS, 2021). This rapid population growth and the expanded base of the population pyramid exacerbate the challenge of providing decent jobs or other economic opportunities especially to young people. As a result, unemployment and underemployment rates are relatively high. According to the Nigerian National Bureau of Statistics (NBS, 2021), the unemployment rate increased from 6% in the last quarter of 2014 to 33% in the last quarter of 2020. During the same period, the underemployment rate rose from 18% to 23%. Moreover, there is significant regional heterogeneity. In the last quarter of 2020, the unemployment rate ranged from 12% in Osun State

[5] Estimated using yearly data from the World Bank World Development Indicators

to 57% in Imo State, while the underemployment rate ranged from 5% in Lagos State to 44% in Benue State (NBS, 2021).

Numerous socioeconomic, cultural, financial, and administrative factors impede Nigerians' access to education (Alabi et al., 2014; Garba, 2014; Nwogu, 2015) and thus prevent a significant portion of the workforce from accessing decent economic opportunities. The NBS (2021) reported that out of the 69 million people in the labor force in the last quarter of 2020, about 21 million had no education, which represented 30% of the labor force. Out of these 21 million people, 29% were unemployed and 31% underemployed. Moreover, 50% of the labor force had an elementary or secondary certificate, and 19% had a post-secondary school certificate. Additionally, the shares of unemployment and underemployment are slightly higher for women (35% and 24% respectively) than for men (32% and 22%, respectively). Finally, according to the International Labor Organization (ILO), the services sector is the country's largest employer, with 47.6% of the total employment in 2019. It is followed by the agricultural sector (38.6%) and the industry (13.8%) (ILO, 2021). However, these employments are mostly informal. Using data from a 2013 socioeconomic survey, the ILO estimated that up to 92.9% of the total employment in Nigeria is informal (ILO, 2018).

Overall, the relatively high extent of unemployment, underemployment, informal employment, along with poor education suggest that a significant proportion of the population is vulnerable to poverty and food insecurity. Because conflicts can damage these already vulnerable jobs, they can push those exposed below the poverty line and into food insecurity.

4.2.2. Conflicts in Nigeria

Many historical and structural sources of tension (e.g., religious and ethnic heterogeneity, uneven regional development dating back to the colonial period, climate change, desertification, and mismanagement of fertile and grazing lands) fuel violence between different socioeconomic groups in the Nigerian population (see Bienen, 1986; Harnischfeger, 2008; Lenshie et al., 2021; Osinubi and Osinubi, 2006; Paden, 2015). They foster the birth and spread of several armed groups that perpetrate violent events in different regions. These threats include the Boko Haram Islamist insurgency in the northeast, the conflict between cattle herders and farmers spreading from the central belt southward, the Niger Delta Vigilante, the Indigenous People of Biafra in the southeast, the Shia Islamic Movement of Nigeria in central Nigeria, and Islamic State West Africa Province in the northeast.

Figure 9 shows that the number of organized violent events in Nigeria has increased exponentially over the past two decades, as has the number of reported fatalities. The two heat maps in Figure 10 show how the spatial distribution of conflicts events changed over the years. They suggest that, from 2001 to 2021, the number of states affected by conflicts increased significantly and that more conflict events are being reported in the affected areas. These conflicts create a humanitarian crisis, displace millions of people, limit the range of livelihood activities available, and exacerbate poverty and food insecurity (FAO, 2017a; International Crisis Group, 2018; WFP, 2017).

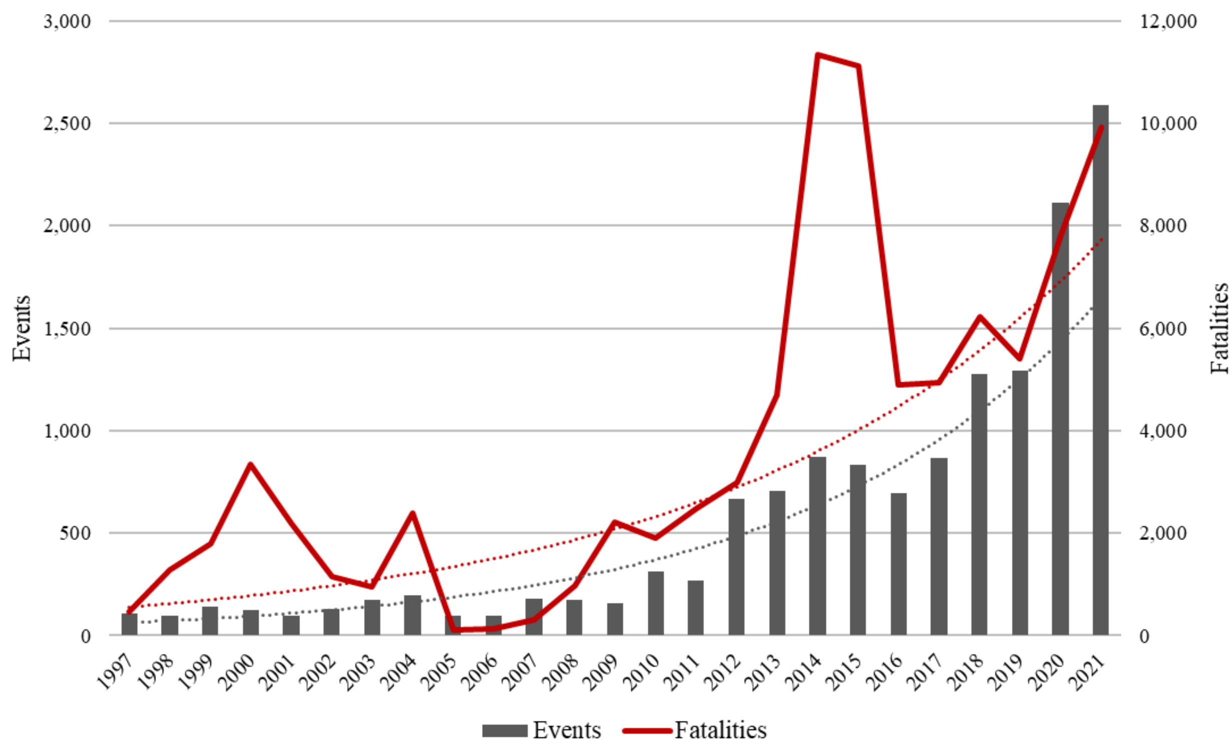

Figure 9: Total number of organized violent events in Nigeria, reported fatalities, and exponential trends for the period 1997-2021
Source: Author's calculation from ACLED data

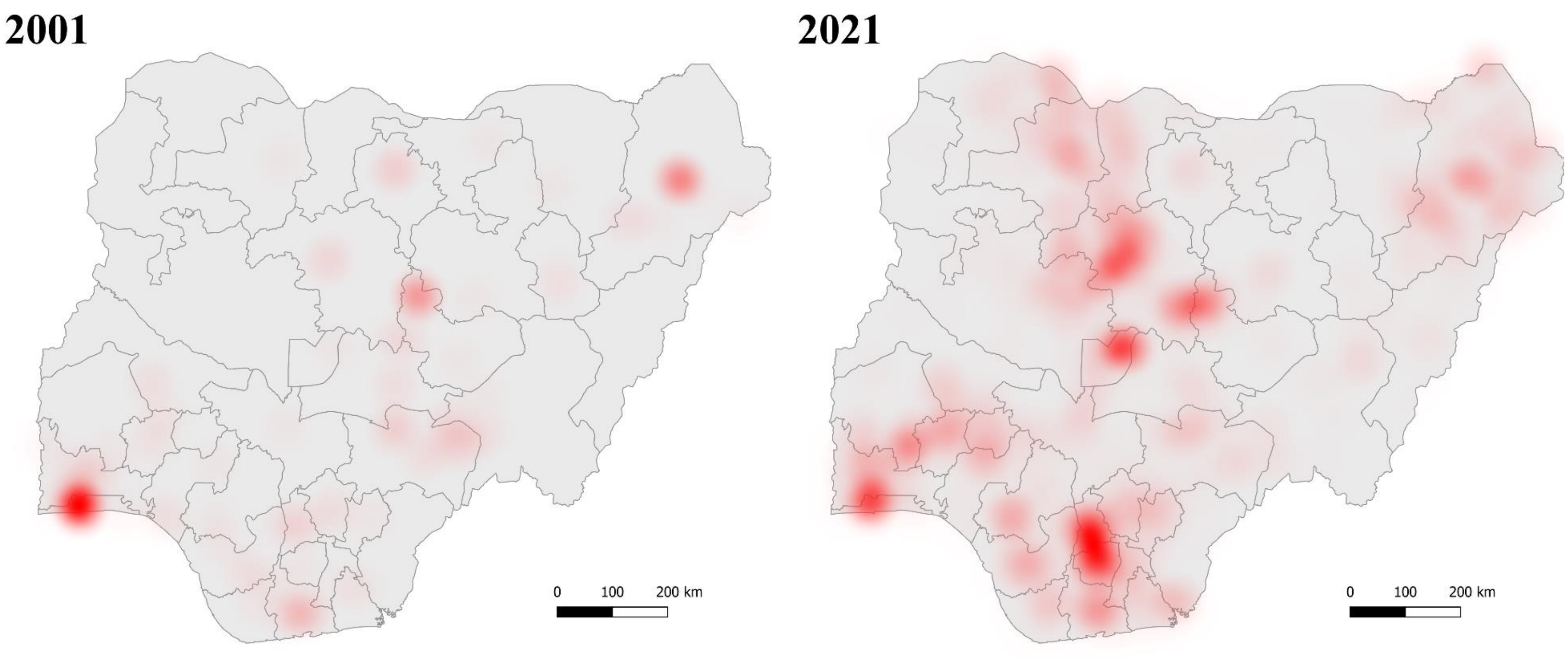

Figure 10: Heat maps of conflicts events in Nigeria in 2001 and 2021
Source: Author’s calculations based on the ACLED dataset

4.3. Conceptual framework

To inform the empirical analysis, this section presents a model that explains how conflict affects the allocation of labor to family farm enterprises, family non-farm enterprises, and employment with others. Following the derivations of Singh and Strauss (1986), the recent adaptation by Mathenge & Tschirley (2015) and extending it to multiple occupations, an agricultural household jointly optimizes consumption, production, and employment decisions and chooses the optimal amount of labor supplied to family farm enterprises (L_f), family non-farm enterprises (L_n), and employment with others (L_e). These labor supply decisions can be represented as:

$$L_j = L_j\left(w_e, P_x, P_y, I, H, Z\right), \quad j \in \{f, n, e\} \tag{63}$$

where w_e is the wage from employment, P_x and P_y are the vectors of *adjusted* inputs and outputs prices, respectively. The prices are adjusted for the cost of accessing inputs and outputs markets, respectively (i.e., adjusted price of output equals output price minus cost of getting the product from the farm to the output market; adjusted price of input equals input price plus cost of getting the product from the input market to the farm). I is the household's wealth, H is the household's human capital, and Z represents the vector of other households' characteristics including the state of the local economy and labor market characteristics.

4.3.1. Pathways from conflicts to employment wage

In each sector, the wage offer (w_e) is a function of the human capital (H), the aggregates labor demand (D_L) and supply (D_S), labor market characteristics, and the state of the local economy (Z). The aggregate labor demand (D_L) is driven by the aggregate demand for goods and services, which is, in turn, driven by the aggregate income in the area. In the agriculture sector, the negative effects of conflicts on wages and demand for hired labor (Adelaja & George, 2019a) can be explained by their effects on the aggregate income in the area. Indeed, conflicts affect productivity, output, and profitability (Adelaja & George, 2019a; Arias et al., 2019; Awodola & Oboshi, 2015; Sidney et al., 2017), which are determinants of this aggregate income. Moreover, the conflict-induced income instability (Brück et al., 2019; Odozi & Oyelere, 2019) can be reflected at the aggregate level. In addition to their effects on agriculture, conflicts disrupt the revenues of firms operating in the manufacturing and service sectors (del Prete et al., 2021), which are components of aggregate income. Forced displacements induced by conflicts or other shocks trigger labor supply (D_S) shocks in both areas of origin and destination of the displaced people. As a result, they have disruptive effects on employment and wages (George & Adelaja, 2021; Verme & Schuettler, 2021). They also reduce agricultural production (George & Adelaja, 2021), thereby lessening the aggregate income.

Hence, they are many pathways through which conflicts may affect the wage offer. As a result, the wage offer is represented as $w_e = w_e(D_L(C), D_S(C), H, Z)$, where C stands for the degree of exposure of the household to conflicts.

4.3.2. Pathways from conflicts to input and output prices

In areas affected by conflicts, farmland abandonments, reductions in crops productivities and total output (Adelaja & George, 2019a) can cause a leftward shift of the market supply of agricultural products. In parallel, forced displacements can cause a leftward shift of the market demand because many consumers abandoned the market. These potential effects on both the supply and demand sides cause output prices to change in unpredictable directions. Indeed, the directions and amplitude of changes in output prices depend on the elasticities and the extent of the shifts of the market supply and demand.

The reduction and instability in revenues, the prevailing climate of uncertainty and fear due to exposure to conflicts can decrease the demand for farm inputs and impede access to land, human capital, and other productive assets (Adelaja & George, 2019a; Brück et al., 2019; Eme et al., 2014; Odozi & Oyelere, 2019; van den Hoek, 2017). Additionally, inputs availability is reduced in presence of conflicts because of disruptions along their supply chains. Indeed, terrorists reportedly attack fertilizer factories, input and output storage facilities and transportation systems, farm(Adelaja & George, 2019a; Kah, 2017; Kimenyi et al., 2014; van den Hoek, 2017)t al., 2014; van den Hoek, 2017).

All these disruptions amount to higher costs of accessing inputs and outputs markets. The augmented scarcity of inputs is captured by a rise in their prices. In areas hosting forcibly displaced people, the increased consumer demand attributable to savings of migrants, influx of aid, and increased public spending can lead to price changes in the short run (Verme & Schuettler, 2021). One can also extend this reasoning to manufacturing and services since there are also evidence that conflicts affect the performance of firms operating in these sectors (del Prete et al., 2021).

Hence, adjusted input and output prices are functions of the degree of exposure to conflicts. This relationship is represented as $P_x(C)$ and $P_y(C)$.

4.3.3. Effects of conflicts on labor supply decisions

To sum up the two subsections above, conflicts affect the demand and supply in labor, inputs, and output markets, thereby disrupting their equilibrium prices, let alone their effects on the cost of accessing these markets. Hence, the optimal labor supplies can be reformulated as follows:

$$L_j = L_j\left[w_e\big(D_L(C), D_S(C)\big), P_x(C), P_y(C), \Omega\right], \quad j \in \{f, n, e\} \tag{64}$$

where $\Omega = \{I, H, Z\}$ is the set of factors that are fixed during the period of analysis. The *immediate* impact of increased exposure to conflicts on the labor supply to occupation j is:

$$\frac{\partial L_j}{\partial C} = \frac{\partial L_j}{\partial w_e}\frac{\partial w_e}{\partial D_L}\frac{\partial D_L}{\partial C} + \frac{\partial L_j}{\partial w_e}\frac{\partial w_e}{\partial D_S}\frac{\partial D_S}{\partial C} + \frac{\partial L_j}{\partial P_x}\frac{\partial P_x}{\partial C} + \frac{\partial L_j}{\partial P_y}\frac{\partial P_y}{\partial C}, \quad j \in \{f, n, e\} \tag{65}$$

$$\frac{\partial L_j}{\partial C} = \frac{\partial L_j}{\partial w_e}\left[\frac{\partial w_e}{\partial D_L}\frac{\partial D_L}{\partial C} + \frac{\partial w_e}{\partial D_S}\frac{\partial D_S}{\partial C}\right] + \frac{\partial L_j}{\partial P_x}\frac{\partial P_x}{\partial C} + \frac{\partial L_j}{\partial P_y}\frac{\partial P_y}{\partial C}, \quad j \in \{f, n, e\} \tag{66}$$

$\frac{\partial L_j}{\partial w_e}$ captures how the increase in the wage from employment impacts labor supply to j. It depends on factors such as the number of household members, individual members' employability and marginal product in agriculture, manufacturing, and services, all of which depend on their human capital. It also depends on the extent to which the change in employment wage affect the financial attractiveness of the employment option compared to other occupations. $\frac{\partial w_e}{\partial D_L}\frac{\partial D_L}{\partial C}$ and $\frac{\partial w_e}{\partial D_S}\frac{\partial D_S}{\partial C}$ represent the effects of conflicts on the wage employment through the changes in labor demand and supply, respectively. $\frac{\partial P_x}{\partial C}$ and $\frac{\partial P_y}{\partial C}$ capture how conflicts affect adjusted input and output prices, respectively. The earlier discussion suggests that $\frac{\partial P_x}{\partial C} \geq 0$ because of the increased scarcity in input prices and higher costs of reaching markets. However, the sign of $\frac{\partial P_y}{\partial C}$ is hardly predictable. $\frac{\partial L_j}{\partial P_x}$ and $\frac{\partial L_j}{\partial P_y}$ are the direct effects of the rises in input and output prices on the labor supply to occupation j. It depends on how the increased prices change the profitability of each occupation or financial attractiveness of each occupation relatively to the others, the number of household members, and their employability in each sector. The previous two sub-sections explain the economic processes underlying these partial effects.

4.4. Empirical framework

4.4.1. Data sources

The data used in the empirical analysis result from the spatial join of the datasets from the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) conducted in Nigeria in collaboration with the Nigerian Bureau of Statistics (NBS) and the Armed Conflict Location and Event Data (ACLED) Project (Raleigh et al., 2010). As part of the Nigeria GHS, four waves of data collection were conducted in 2010-11, 2012-2013, 2015-2016, and 2018-2019, collecting socioeconomic information for a panel of 5,000 households as well as their geographical coordinates. Furthermore, data was collected during both post-planting and post-harvest seasons. Among other information, the ACLED dataset provides the dates, geographical coordinates, and number of fatalities of political violence and protest events (Raleigh et al., 2010).

4.4.2. Construction of the dependent variables

During the GHS and in each season, households' members[6] were asked individually (1) whether they worked on a farm owned or rented by a member of their household during the past 7 days, (2) whether they worked on their own account or in a business enterprise belonging to them or another household member during the past 7 days, and (3) whether they worked for someone who is not a member of their household during the past 7 days. Using the answers to these three questions, the following binary variables are created: 'WorkedHouseholdFarm', 'WorkedHouseholdEnterprise', and 'WorkedEmployment'. They take on the value 1 if the individual works on the family farm enterprise, family non-farm enterprise, and employment with others, respectively, and 0 otherwise. Next, the variable 'WorkDiversification' is created by

[6] In this study, the sample is restricted to individuals who are at least five years old

summing the three previous variables. A higher value of ‘WorkDiversification’ indicates that the individual is involved in more types of work.

The respondents were also asked in which sector was their primary employment in the last 7 days. The responses to this question are used to create the binary variables ‘WorksInAgri’, ‘WorksInManufacture’, and ‘WorksInServices’ that indicate whether the individual’s primary employment is in agriculture, manufacturing, or services, respectively. The sub-sectors included in services are professional, scientific, and technical activities; electricity, water, gas and waste; construction; transportation; buying and selling; financial, insurance, and real estate services; personal services; education; health; and public administration.

However, there were changes in the ways this question was asked across the waves which might influence the results. Specifically, in wave 1 and 2, this question was asked to anyone who responded ‘Yes’ to the any of the questions (1), (2), and (3) aforementioned. In wave 3, it was asked only to those who reported that they have done any wage or salaried work during the last 7 days. In wave 4, it was only asked to those who responded ‘Yes’ to (3), i.e., those who reported that they had an off-farm employment during the last 7 days. These changes can explain the drop in the number of respondents to questions related to employment and the drop in the share of individuals who reported being employed in agriculture observed from wave 2 to 3 (see Table 13). To avoid bias due to significant change in the composition of the sample, only waves 1 and 2 are used when it comes to estimating the impacts of conflicts on sectoral employment choices. Since there is no change in the questions related to the types of work, all waves are used to study them.

Additionally, variables ‘AgriHoursPP’ and ‘AgriHoursPH’ represent the number of hours per week the individual worked in the agricultural employment during the planting and harvesting seasons, respectively. The variables ‘ManufactureHoursPP’, ‘ManufactureHoursPH’, ServicesHoursPP and ServicesHoursPH are the corresponding variables for the sectors of manufacture and services, respectively.

4.4.3. Measurement of conflicts

An individual's household exposure to conflicts is measured using the number of fatalities recorded within 5 km of the household. This measure is computed using the latitude, longitude, date of occurrence, and the number of fatalities for each conflict event as provided by the ACLED dataset. The information from the ACLED dataset is then spatially joined with the GHS dataset in computing short and long-term measures of conflict exposure. The short-term measure is the number of fatalities recorded 12 months before GHS data collection. The long-term measure is the number of fatalities recorded from 1997 to the month before GHS data collection. The short-term measure is more appropriate for investigating the effects of ongoing conflicts (see, for instance, Bertoni et al., 2019; George et al., 2020; Odozi and Uwaifo Oyelere, 2021). However, the long-term measure (see, for instance, Odozi & Uwaifo Oyelere, 2021) captures the vulnerability of the area of residence of the individual to conflicts since this vulnerability results from levels of socioeconomic factors that exacerbate anger, such as poverty, the lack of economic opportunities, and the difficult access to basic services (see Gassebner and Luechinger, 2011; Kavanagh, 2011). Appendices A3 (tables 45 and 46) present the dates of GHS data collection and the periods considered for short and long-term measures of conflict exposure, respectively. Note that the conflict measurement periods are specific to waves and seasons within the waves.

To investigate how individuals' sensitivity to violent events changes with the distance to these events, I also compute the number of fatalities recorded within 20 and 40 km of individuals' households. The areas defined by the 5, 20, and 40 km radii are typically named *buffer zones*. Bertoni et al. (2019) used the buffer zones approach to study the impact of the Boko Haram insurgency on educational outcomes in Nigeria. Yet another alternative measurement of conflict used in this analysis is the number of fatalities recorded within the Local Government Areas (LGA) where the individuals reside. The LGA-based approach is common in the literature (see, for instance, Adelaja and George, 2019a, 2019b; George et al., 2020; Odozi and Uwaifo Oyelere, 2021). Comparing the results obtained using the buffer-based and LGA-based measurements enables testing the presence of the so-called *edge effects* or *boundary effects* (I. Yamada, 2009). In this study, *edge effects* mean that individuals located near an LGA's border are influenced not only by events occurring within their LGA but also by those occurring in contiguous LGAs. When estimating the impact of conflicts using LGA-based measures for such individuals, one ignores the influence of conflict events recorded outside the individuals' LGAs, but directly impact them. Therefore, LGA-based measures can lead to biased empirical results. Part (a) of Figure 11 illustrates these types of edge effects.

Table 12 presents the definition of variables used in this study and Table 13 provides their descriptive statistics.

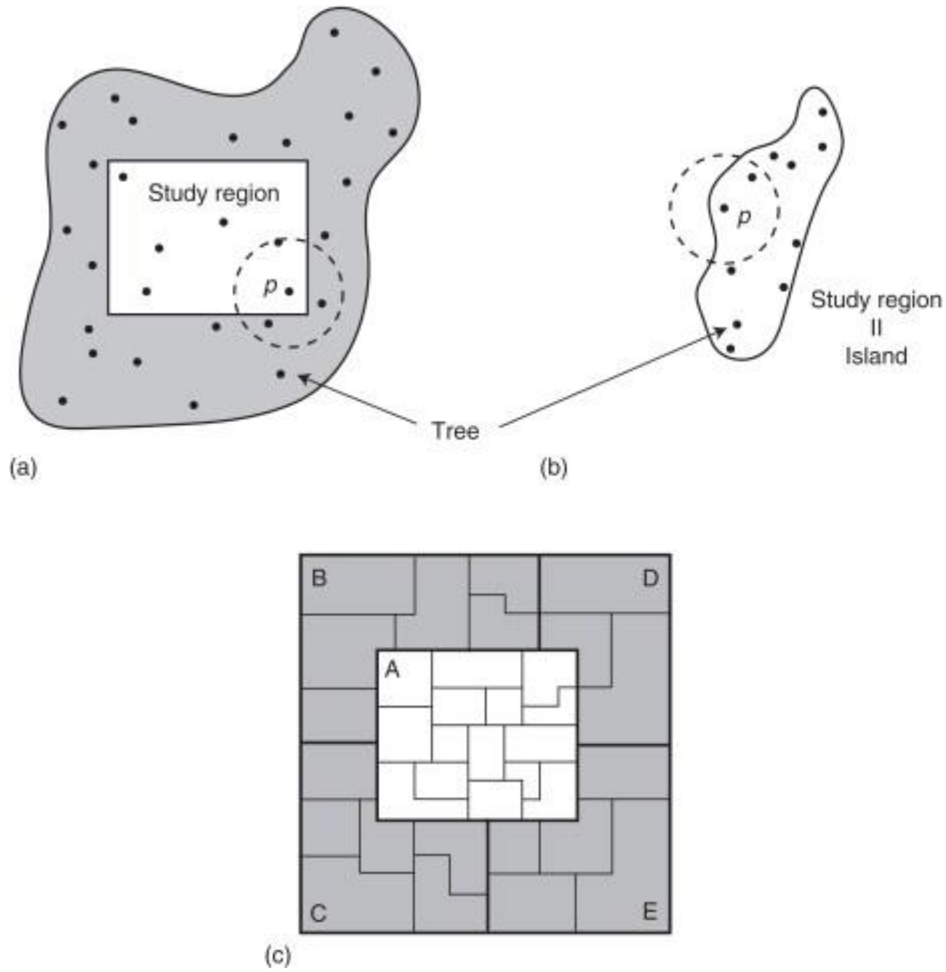

Figure 11: Illustration of the edge effects
Source: (I. Yamada, 2009)

Table 12: Variables' definitions

Dependent variables	
WorkedHouseholdFarm	Whether the individual works on the household's farm
WorkedHouseholdEnterprise	Whether the individual works in a household's enterprise
WorkedEmployment	Whether the individual has an employment
WorkDiversification	Number of type of activities the individual is involved in
WorksInAgri	Whether the individual works in agriculture
AgriHoursPP	Number of hours per week worked in agriculture during planting season
AgriHoursPH	Number of hours per week worked in agriculture during harvesting season
WorksInManufacture	Whether the individual works in manufacture
ManufactureHoursPP	Number of hours per week worked in manufacture during planting season
ManufactureHoursPH	Number of hours per week worked in manufacture during harvesting season
WorksInServices	Whether the individual works in services
ServicesHoursPP	Number of hours per week worked in services during planting season
ServicesHoursPH	Number of hours per week worked in services during harvesting season
Shocks	
fatalities_ST_5km_PP	Number of fatalities occurring during the short-term period and the planting season in an area of radius 5 km around the individual's household
fatalities_ST_5km_PH	Number of fatalities occurring during the short-term period and the harvest season in an area of radius 5 km around the individual's household
fatalities_ST_20km_PP	Number of fatalities occurring during the short-term period and the planting season in an area of radius 20 km around the individual's household
fatalities_ST_20km_PH	Number of fatalities occurring during the short-term period and the harvest season in an area of radius 20 km around the individual's household
fatalities_ST_40km_PP	Number of fatalities occurring during the short-term period and the planting season in an area of radius 40 km around the individual's household
fatalities_ST_40km_PH	Number of fatalities occurring during the short-term period and the harvest season in an area of radius 40 km around the individual's household
fatalities_LGA_ST_PP	Number of fatalities occurring during the short-term period and the planting season in the LGA where the individual resides
fatalities_LGA_ST_PH	Number of fatalities occurring during the short-term period and the harvest season in the LGA where the individual resides
fatalities_LT_5km_PP	Number of fatalities occurring during the long-term period and the planting season in an area of radius 5 km around the individual's household
fatalities_LT_5km_PH	Number of fatalities occurring during the long-term period and the harvest season in an area of radius 5 km around the individual's household
fatalities_LT_20km_PP	Number of fatalities occurring during the long-term period and the planting season in an area of radius 20 km around the individual's household
fatalities_LT_20km_PH	Number of fatalities occurring during the long-term period and the harvest season in an area of radius 20 km around the individual's household
fatalities_LT_40km_PP	Number of fatalities occurring during the long-term period and the planting season in an area of radius 40 km around the individual's household
fatalities_LT_40km_PH	Number of fatalities occurring during the long-term period and the harvest season in an area of radius 40 km around the individual's household
fatalities_LGA_LT_PP	Number of fatalities occurring during the long-term period and the planting season in the LGA where the individual resides
fatalities_LGA_LT_PH	Number of fatalities occurring during the long-term period and the harvest season in the LGA where the individual resides

Table 12 (cont'd)

Control variables	
Female	The individual is a female
Age	Age of the individual
Age_sq	Age of the individual squared
Education	Number of years of education of the individual
AgeHead	Age of the household head
AgeHead_sq	Age of the household head squared
LandSize	Agricultural land size
LivestockValue	Value of the livestock
NbChildren	Number of children (7-15 years old) in the household
AssetValue	Value of assets (1,000 Naira)
DistMarket	Household distance to nearest market
Precipitation	Annual Precipitation
HighSkilled	Whether the individual is highly skilled (i.e., has completed the secondary school)

Table 13: Descriptive statistics

	Wave 1		*Wave 2*		*Wave 3*		*Wave 4*	
	N	*Mean*	*N*	*Mean*	*N*	*Mean*	*N*	*Mean*
Dependent variables								
WorkedHouseholdFarm	23,903	0.37	24,352	0.33	24,686	0.38	24,889	0.46
WorkedHouseholdEnterprise	23,903	0.25	24,353	0.24	24,681	0.26	24,889	0.28
WorkedEmployment	23,907	0.10	24,351	0.08	24,685	0.07	24,889	0.08
WorkDiversification	23,909	0.72	24,353	0.65	24,686	0.71	24,889	0.82
WorksInAgri	13,344	0.64	12,434	0.64	1,664	0.07	2,060	0.08
AgriHoursPP	13,344	20.23	12,434	18.65	1,664	1.38	2,060	1.57
AgriHoursPH	13,344	15.39	12,434	15.38	1,664	1.21	2,060	1.29
WorksInManufacture	13,344	0.08	12,434	0.09	1,664	0.06	2,060	0.07
ManufactureHoursPP	13,344	2.01	12,434	2.17	1,664	1.48	2,060	1.66
ManufactureHoursPH	13,344	2.02	12,434	2.64	1,664	1.82	2,060	2.07
WorksInServices	13,344	0.48	12,434	0.48	1,664	0.90	2,060	0.88
ServicesHoursPP	13,344	17.98	12,434	15.97	1,664	26.72	2,060	23.51
ServicesHoursPH	13,344	17.23	12,434	17.94	1,664	32.11	2,060	24.62
Shocks								
fatalities_ST_5km_PP	23,954	1.30	24,900	3.12	25,136	8.91	25,271	1.68
fatalities_ST_5km_PH	23,954	1.21	24,900	3.30	25,136	5.36	25,271	1.03
fatalities_ST_20km_PP	23,954	7.89	24,900	12.18	25,136	26.15	25,271	11.86
fatalities_ST_20km_PH	23,954	4.77	24,900	11.32	25,136	19.66	25,271	7.98
fatalities_ST_40km_PP	23,954	16.18	24,900	22.26	25,136	56.52	25,271	31.83
fatalities_ST_40km_PH	23,954	10.84	24,900	21.36	25,136	36.58	25,271	25.15
fatalities_LGA_ST_PP	23,954	4.20	24,897	5.92	25,131	16.50	25,271	6.20
fatalities_LGA_ST_PH	23,954	2.80	24,897	6.37	25,131	14.57	25,271	5.21
fatalities_LT_5km_PP	23,954	22.44	24,900	27.88	25,136	45.50	25,271	45.33
fatalities_LT_5km_PH	23,954	22.89	24,900	29.38	25,136	46.65	25,271	45.71
fatalities_LT_20km_PP	23,954	85.89	24,900	95.44	25,136	162.82	25,271	223.17
fatalities_LT_20km_PH	23,954	87.16	24,900	99.65	25,136	168.46	25,271	226.61
fatalities_LT_40km_PP	23,954	202.39	24,900	233.02	25,136	354.15	25,271	452.76
fatalities_LT_40km_PH	23,954	206.12	24,900	241.37	25,136	364.96	25,271	463.60
fatalities_LGA_LT_PP	23,954	35.08	24,897	46.83	25,131	88.27	25,271	116.70
fatalities_LGA_LT_PH	23,954	35.92	24,897	49.09	25,131	92.35	25,271	119.17

Table 13 (cont'd)

Control variables

Female	23,379	0.50	23,848	0.51	24,283	0.50	23,886	0.51
Age	23,351	27.07	23,097	27.18	23,844	27.33	23,886	27.08
Age_sq	23,351	1,096.45	23,097	1,110.61	23,844	1,123.09	23,886	1,099.52
Education	17,082	7.78	17,372	7.91	17,476	7.94	18,303	7.99
AgeHead	23,897	50.63	23,469	52.01	25,131	52.75	25,273	51.08
AgeHead_sq	23,897	2,752.44	23,469	2,887.64	25,131	2,961.21	25,273	2,799.12
LandSize	23,954	1.11	24,911	1.05	25,136	0.95	25,286	1.54
LivestockValue	23,954	167,659.23	24,911	201,728.18	25,136	204,975.05	25,286	205,895.63
NbChildren	23,948	2.02	24,453	2.07	25,131	2.24	25,286	2.20
AssetValue	23,693	146.82	24,581	132.13	24,993	355.53	25,280	386.09
DistMarket	23,954	67.51	24,899	67.62	25,136	68.62	25,271	66.08
Precipitation	23,954	1,413.19	24,899	1,387.44	25,136	1,382.06	25,271	1,409.77
HighSkilled	17,082	0.09	17,372	0.09	17,476	0.09	18,303	0.11

4.4.4. Empirical strategy

Fixed-effects regressions are used to quantify the effects of conflict exposure on the outcomes of interest. The empirical model can be represented as:

$$y_{igst} = \alpha + \beta fatalities_{gt} + \gamma \boldsymbol{X}_{igst} + \mu_i + \tau_t + \eta_s + \lambda_{st} + \epsilon_{igst} \quad (67)$$

where the indices i, g, s, and t represent the individual, the geographic area of residence, which can be a buffer zone or an LGA as explained in section 4.4.3, the state where the individual resides, and the survey year, respectively. $fatalities_{gt}$ stands for the number of fatalities recorded in the geographic area g where the individual resides in survey year t. $\boldsymbol{X}_{igst}$ is a vector of control variables. μ_i, τ_t, η_s, and λ_{st} are the individual, survey year, state, and state-year fixed effects, respectively. Standard errors are clustered at the individual level.

The control variables include individual and household level variables that have been shown to determine individuals' type of work. Controlling for household level variables is important since decision about individuals' occupation are partly taken at the household level. The controls variables used include the gender of the individuals, their age, age squared, and number of years of education. Household-level controls include the age of the household head, the square of the age of the household head, the size of farmland, the value of the livestock, the number of children in the household, the value of assets, the distance to the nearest market, and the annual rainfall. Since adverse weather conditions are reported to increase the occurrence of conflicts (Akresh, 2016) and also determine the individuals' labor allocation (Branco & Féres, 2021; Cameron & Worswick, 2003; Cunguara et al., 2011; Jessoe et al., 2018; Kijima et al., 2006; Lamb, 2003; Mathenge & Tschirley, 2015; Rose, 2001), it is necessary to control for weather conditions to avoid endogeneity of $fatalities$.

Reverse causality may also cause endogeneity since non-participation in economic activities may reflect the lack of economic opportunities which in turn fuels anger and favors conflicts. However, as discussed by George et al. (2020), this reverse causality is an issue occurring at more aggregated levels such as regional and national levels and is less likely at very disaggregated levels such as the individual level used in this article. Additional controls include state and state-wave fixed effects which partially capture the economic conditions and trends in economic conditions at the state level, respectively.

Individual fixed effects also control for time-invariant, unobserved individual-level factors that simultaneously explain individual occupational choices and exposure to conflict. Temporal variations or shocks that affect all individuals' occupational choices are controlled using survey year fixed effects. That can also control such shocks that raise the likelihood of violent events. Given the fixed-effect nature of the empirical model, the coefficient β will capture the causal effect of $fatalities$ on the outcomes of interest if there are no time-varying unobservables that simultaneously determine the number of fatalities and the outcomes of interest, conditional on the vector of control variables.

To examine the differences in the effects of $fatalities$ between men and women, the empirical model is also estimated using the subsets of men and women taken separately. The difference between skilled and unskilled labor is based on the years of education. Skilled laborers are those who completed more years of education than the number required to complete secondary school.

4.5. Results and discussion

The empirical results are presented next.

4.5.1. Effects of conflicts on the types of work: family farm enterprises, family non-farm enterprises, and employment with others

First, the impacts of conflict exposure on individuals' participation in family farm and non-farm enterprises and employment with others are explored, along with the impact on the diversification index. The focus is on the number of fatalities recorded within 5 km of individuals' households. Table 14 and Table 15 present the estimated results of the effects of short and long run measures of conflicts, respectively, along with the coefficients of control variables.

In the short run (see Table 14), the rise in the number of fatalities is found to have significantly reduced the probability of participating in family farm enterprises. This suggests that individuals abandon family farm activities, probably due to the fear and uncertainty associated with conflicts and the stresses on agricultural input and output supply chains. This also corroborates the substantial farmland abandonment identified in the literature (see, for example, Adelaja and George, 2019b). In contrast, increased exposure to conflicts significantly increases the probability of being employed outside the household, including agriculture and non-agricultural jobs, such as manufacturing and services. This suggests that non-farm employment is less exposed to violent events and provided alternative sources of income for those whose livelihoods were disrupted by conflicts. Altogether, the impacts on the three types of work indicate that individuals abandon households' farm enterprises and tend to substitute for these activities with employment. This finding is consistent with several articles which found that individuals or households respond to conflicts or other shocks by getting more involved in off-farm employment (e.g., Branco and Féres, 2021; Cameron and Worswick, 2003; Cunguara et al., 2011; Fernández et al., 2014; Mathenge and Tschirley, 2015).

However, there is no significant effect of conflict exposure on family non-farm enterprises, suggesting that non-farm enterprises are less vulnerable to disruptions from conflict. Since there is a variety of non-farm enterprises than can be undertaken by households, more precise interpretation of this result must consider the nature of these activities. Similarly, there is no significant effect on the diversification index, suggesting that conflicts do not facilitate diversification. One explanation for this is that while the allocation of time between alternative sources of income changes, the number of activities does not necessarily change. From Table 15, all types of occupation are significantly affected by long-term exposure to conflicts. That is, participation in family farm enterprises is negatively affected, while participation in family non-farm enterprises and employment outside the household are positively affected. Again, the diversification index is not significantly affected.

Comparing the short and long-term effects, it appears that conflicts consistently retard farm household activities in both the short run and long run. However, while conflicts only encourage off-farm job seeking in the short run, they encourage both off-farm job seeking and participation in family non-farm activities in the long-run. These differences are explained as follows. First, a place that is under long-term conflict perturbation will probably be more likely to respond to this shock by pursuing non-farm activities than a place whose exposure has been relatively minimal. Second, moving from one occupation or sector to another (e.g., starting a family non-farm enterprise to replace disrupted family farm enterprises) is an adjustment that may take more time than the short run allows. Third, areas persistently affected by conflicts are more likely to attract humanitarian assistance from domestic and foreign sources, which may help create employment opportunities in non-farm sectors.

The coefficients of control variables have expected signs when they are found to be statistically significant. For instance, there is a concave relationship between the individuals' age and the labor outcomes, which is indicated by the positive sign of the coefficient associated with the variable age and the negative sign of the coefficient associated with the square of age.

Moreover, the increased number of children in the household is also found to incentivize the involvement in more type of work, especially agriculture, which also makes intuitive sense.

Table 14: Short-term effects of conflicts on the types of work

	(1) Family farm enterprises	(2) Family non-farm enterprises	(3) Employment	(4) Diversification
Short-term fatalities within 5 km	-0.000294***	4.88e-05	0.000140**	-0.000105
	(6.34e-05)	(7.76e-05)	(6.43e-05)	(0.000121)
Female	-0.0253	-0.0190	-0.0438	-0.0881
	(0.0517)	(0.0360)	(0.0331)	(0.0693)
Age	0.0200***	0.0174***	0.00786***	0.0452***
	(0.00152)	(0.00139)	(0.00106)	(0.00240)
Age squared	-0.000246***	-0.000188***	-8.89e-05***	-0.000523***
	(1.76e-05)	(1.67e-05)	(1.36e-05)	(3.00e-05)
Years of education	0.00130	-0.000945	0.00100	0.00136
	(0.000951)	(0.000900)	(0.000685)	(0.00149)
Age of household head	-0.00509***	-0.00514***	-0.00264**	-0.0129***
	(0.00184)	(0.00169)	(0.00130)	(0.00282)
Age of household head squared	5.39e-05***	3.36e-05**	2.21e-05*	0.000110***
	(1.68e-05)	(1.52e-05)	(1.19e-05)	(2.61e-05)
Household's land size	0.000346	-0.000239	-0.000304	-0.000197
	(0.000315)	(0.000149)	(0.000239)	(0.000327)
Household's livestock value	-3.73e-10	-2.44e-09	-3.33e-09**	-6.14e-09
	(3.84e-09)	(3.52e-09)	(1.62e-09)	(6.86e-09)
Number of children in the household	0.00615***	0.000248	-8.65e-05	0.00631**
	(0.00208)	(0.00176)	(0.00129)	(0.00301)
Value of household's assets	-1.47e-06	2.39e-07	-6.56e-07	-1.89e-06
	(9.28e-07)	(3.90e-07)	(6.35e-07)	(1.42e-06)
Household's distance to nearest market	0.000257	-0.000381**	3.17e-05	-9.24e-05
	(0.000180)	(0.000164)	(0.000105)	(0.000259)
Annual Precipitation	-1.59e-05	-5.75e-05	0.000119	4.52e-05
	(6.58e-05)	(9.53e-05)	(7.43e-05)	(0.000101)
Constant	0.384	0.102	-0.115	0.370
	(0.237)	(0.279)	(0.221)	(0.384)
Observations	67,357	67,356	67,358	67,360
R-squared	0.100	0.045	0.019	0.103

Notes: Each column represents a regression. Individual, state, and state-wave fixed effects are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 15: Long-term effects of conflicts on the types of work

	(1) Family farm enterprises	(2) Family non-farm enterprises	(3) Employment	(4) Diversification
Long-term fatalities within 5 km	-0.000161***	6.68e-05**	8.80e-05***	-5.75e-06
	(2.19e-05)	(2.67e-05)	(2.50e-05)	(4.01e-05)
Female	-0.0260	-0.0190	-0.0435	-0.0884
	(0.0515)	(0.0360)	(0.0332)	(0.0693)
Age	0.0200***	0.0174***	0.00786***	0.0452***
	(0.00152)	(0.00139)	(0.00106)	(0.00240)
Age squared	-0.000246***	-0.000188***	-8.89e-05***	-0.000523***
	(1.76e-05)	(1.67e-05)	(1.36e-05)	(3.00e-05)
Years of education	0.00132	-0.000951	0.000989	0.00136
	(0.000950)	(0.000900)	(0.000684)	(0.00149)
Age of household head	-0.00512***	-0.00510***	-0.00261**	-0.0128***
	(0.00183)	(0.00169)	(0.00130)	(0.00282)
Age of household head squared	5.43e-05***	3.32e-05**	2.18e-05*	0.000109***
	(1.68e-05)	(1.52e-05)	(1.19e-05)	(2.61e-05)
Household's land size	0.000347	-0.000239	-0.000305	-0.000197
	(0.000316)	(0.000149)	(0.000239)	(0.000327)
Household's livestock value	-1.78e-10	-2.40e-09	-3.40e-09**	-5.98e-09
	(3.83e-09)	(3.51e-09)	(1.62e-09)	(6.84e-09)
Number of children in the household	0.00611***	0.000241	-7.16e-05	0.00628**
	(0.00208)	(0.00176)	(0.00128)	(0.00301)
Value of household's assets	-1.42e-06	2.00e-07	-6.87e-07	-1.91e-06
	(8.94e-07)	(3.76e-07)	(6.54e-07)	(1.44e-06)
Household's distance to nearest market	0.000282	-0.000387**	1.93e-05	-8.54e-05
	(0.000180)	(0.000164)	(0.000105)	(0.000259)
Annual Precipitation	-3.23e-05	-5.10e-05	0.000128*	4.42e-05
	(6.65e-05)	(9.60e-05)	(7.40e-05)	(0.000101)
Constant	0.438*	0.0780	-0.145	0.371
	(0.238)	(0.282)	(0.219)	(0.385)
Observations	67,357	67,356	67,358	67,360
R-squared	0.101	0.046	0.019	0.103

Notes: Each column represents a regression. Individual, state, and state-wave fixed effects are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

4.5.2. Effects of conflicts on sectoral employment choices

The short run impacts of conflict exposure on employment in agriculture, manufacturing, and services sectors are presented in tables 5, 6, and 7, respectively. In each table, column 1 reports the results of regressions where the outcome variable is the probability of being employed in the specified sector. In columns 2 and 3, the outcome variables are the time spent by individuals in the specified sector during the agricultural planting and harvesting seasons, respectively.

The results suggest that conflict significantly reduces the probability of being employed in agriculture but does not significantly affect the time spent in this sector in planting and harvesting seasons (see Table 16). This may suggest greater labor inefficiency as a result of conflict since a reduction in interest and commitment, but no reduction of time commitment is reflective of increased inefficiency (see Adelaja & George (2019a)). In contrast, in the long run, exposure to conflicts does not reduce the probability of being involved in agriculture but increases the time spent on planting (see Table 19). This may reflect the need to compensate for damages to crops and other agricultural products as a result of conflicts.

Turning to manufacturing (see Table 17), no significant effect of conflicts is found on the probability of being employed and the time spent in this sector during the agricultural planting or harvesting season. This suggests that manufacturing activities are less exposed to conflict on the short run. Additionally, the absence of effects observed during the agricultural planting and harvesting seasons suggests that they are few linkages between the manufacturing and agricultural sectors on the short run. However, the increased exposure to conflicts significantly decreases the time spent in service employment during the harvesting season (see Table 18). This might reflect the adverse effects of conflicts on some agricultural related services, especially those provided during the planting season (e.g., transport of seeds and fertilizers). Similar to the short run results, employment in manufacturing was not significantly affected by the long-term exposure to conflicts (see Table 20). Additionally, there is no significantly negative effect of conflicts exposure on the time spent in service employment in the long run (see Table 21).

Table 16: Short-term effects of conflicts on employment in agriculture

	(1) Agriculture	(2) Agriculture hours post-planting	(3) Agriculture hours post-harvest
Short-term fatalities within 5 km	-0.000187**	0.00236	0.00660
	(8.88e-05)	(0.00467)	(0.00648)
Female	0.0416	-6.425	19.04**
	(0.0373)	(8.839)	(9.694)
Age	-0.00221	0.300	-0.0243
	(0.00377)	(0.215)	(0.207)
Age squared	3.39e-05	-0.00422*	-1.02e-05
	(3.89e-05)	(0.00227)	(0.00226)
Years of education	0.000952	-0.119	0.174*
	(0.00149)	(0.0935)	(0.0998)
Age of household head	-0.0106***	-0.334	0.0205
	(0.00384)	(0.213)	(0.252)
Age of household head squared	8.73e-05***	0.00417**	0.000703
	(3.28e-05)	(0.00179)	(0.00214)
Household's land size	3.92e-05	0.0266	0.0261
	(0.000123)	(0.0179)	(0.0174)
Household's livestock value	5.41e-10	2.42e-07	1.44e-06*
	(1.65e-08)	(5.48e-07)	(8.08e-07)
Number of children in the household	0.00583	-0.157	-0.0658
	(0.00429)	(0.272)	(0.265)
Value of household's assets	-4.20e-06	-3.16e-05	0.000229
	(6.35e-06)	(0.000291)	(0.000178)
Household's distance to nearest market	0.000970	-0.118	0.116
	(0.00135)	(0.124)	(0.120)
Annual Precipitation	0.000105	0.000686	0.00980
	(0.000117)	(0.00727)	(0.00823)
Constant	0.676**	30.54*	-19.47
	(0.267)	(18.54)	(19.27)
Observations	16,296	16,296	16,296
R-squared	0.017	0.068	0.048

Notes: Each column represents a regression. Individual, state, and state-wave fixed effects are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 17: Short-term effects of conflicts on employment in manufacturing

	(1) Manufacture	(2) Manufacture hours post-planting	(3) Manufacture hours post-harvest
Short-term fatalities within 5 km	-0.000110	-0.00157	0.00628
	(0.000236)	(0.00862)	(0.00770)
Female	-0.0200	0.269	-0.198
	(0.0138)	(0.569)	(0.698)
Age	0.00169	0.227**	-0.0753
	(0.00264)	(0.0988)	(0.110)
Age squared	-1.91e-05	-0.00241**	0.000448
	(2.76e-05)	(0.00104)	(0.00108)
Years of education	-0.00235	-0.0335	-0.0466
	(0.00150)	(0.0651)	(0.0517)
Age of household head	-0.00864***	-0.151	-0.138
	(0.00305)	(0.0997)	(0.123)
Age of household head squared	7.49e-05***	0.00140*	0.00122
	(2.64e-05)	(0.000794)	(0.00103)
Household's land size	5.75e-05	0.000894	-0.00358
	(7.57e-05)	(0.00382)	(0.00340)
Household's livestock value	6.66e-10	8.95e-08	2.06e-07*
	(4.13e-09)	(1.02e-07)	(1.18e-07)
Number of children in the household	0.000988	-0.0697	0.0454
	(0.00342)	(0.121)	(0.145)
Value of household's assets	-4.66e-08	8.70e-05*	4.58e-05
	(3.21e-06)	(4.96e-05)	(6.32e-05)
Household's distance to nearest market	0.000489	0.0177	0.0613*
	(0.000920)	(0.0282)	(0.0372)
Annual Precipitation	1.44e-06	0.000454	0.00150
	(4.68e-05)	(0.00184)	(0.00215)
Constant	0.260*	-0.716	1.827
	(0.148)	(5.129)	(5.718)
Observations	16,296	16,296	16,296
R-squared	0.039	0.014	0.030

Notes: Each column represents a regression. Individual, state, and state-wave fixed effects are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 18: Short-term effects of conflicts on employment in services

	(1) Services	(2) Services hours post-planting	(3) Services hours post-harvest
Short-term fatalities within 5 km	0.000152	-0.0364**	-0.0104
	(0.000123)	(0.0163)	(0.0153)
Female	0.0194	2.651*	1.252
	(0.0306)	(1.598)	(1.338)
Age	0.0101**	0.923***	0.561**
	(0.00457)	(0.233)	(0.256)
Age squared	-0.000102**	-0.00812***	-0.00608**
	(4.95e-05)	(0.00258)	(0.00275)
Years of education	0.00321	0.0775	0.154
	(0.00203)	(0.126)	(0.127)
Age of household head	0.00241	0.114	-0.132
	(0.00512)	(0.264)	(0.273)
Age of household head squared	-4.86e-05	-0.00203	0.000360
	(4.61e-05)	(0.00221)	(0.00228)
Household's land size	-1.42e-05	-0.0140	-0.0209**
	(0.000484)	(0.0206)	(0.0104)
Household's livestock value	1.37e-08	6.85e-07	1.12e-06
	(1.34e-08)	(5.41e-07)	(8.26e-07)
Number of children in the household	0.00204	0.208	-0.101
	(0.00532)	(0.310)	(0.334)
Value of household's assets	1.06e-06	0.000256	-0.000627
	(5.42e-06)	(0.000457)	(0.000383)
Household's distance to nearest market	-0.00281	0.129	0.137
	(0.00221)	(0.0925)	(0.141)
Annual Precipitation	-0.000206	0.00480	0.00322
	(0.000179)	(0.00793)	(0.00965)
Constant	0.810**	-6.785	2.715
	(0.392)	(18.51)	(21.77)
Observations	16,296	16,296	16,296
R-squared	0.027	0.035	0.028

Notes: Each column represents a regression. Individual, state, and state-wave fixed effects are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 19: Long-term effect of conflicts on employment in agriculture

	(1) Agriculture	(2) Agriculture hours post-planting	(3) Agriculture hours post-harvest
Long-term fatalities within 5 km	-6.00e-05	0.00780**	0.00409
	(5.95e-05)	(0.00324)	(0.00325)
Female	0.0416	-6.416	19.05**
	(0.0372)	(8.844)	(9.697)
Age	-0.00218	0.302	-0.0245
	(0.00377)	(0.215)	(0.207)
Age squared	3.34e-05	-0.00425*	-1.83e-06
	(3.89e-05)	(0.00227)	(0.00226)
Years of education	0.000955	-0.120	0.173*
	(0.00149)	(0.0935)	(0.0998)
Age of household head	-0.0106***	-0.332	0.0212
	(0.00384)	(0.213)	(0.252)
Age of household head squared	8.74e-05***	0.00415**	0.000690
	(3.28e-05)	(0.00179)	(0.00214)
Household's land size	4.01e-05	0.0266	0.0261
	(0.000124)	(0.0179)	(0.0174)
Household's livestock value	5.18e-10	2.55e-07	1.45e-06*
	(1.64e-08)	(5.47e-07)	(8.10e-07)
Number of children in the household	0.00582	-0.162	-0.0676
	(0.00429)	(0.272)	(0.265)
Value of household's assets	-4.19e-06	-3.34e-05	0.000228
	(6.35e-06)	(0.000291)	(0.000178)
Household's distance to nearest market	0.000997	-0.120	0.115
	(0.00135)	(0.124)	(0.120)
Annual Precipitation	0.000107	0.000699	0.00978
	(0.000117)	(0.00727)	(0.00824)
Constant	0.671**	30.30	-19.49
	(0.267)	(18.49)	(19.26)
Observations	16,296	16,296	16,296
R-squared	0.017	0.069	0.049

Notes: Each column represents a regression. Individual, state, and state-wave fixed effects are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 20: Long-term effects of conflicts on employment in manufacturing

	(1) Manufacture	(2) Manufacture hours post-planting	(3) Manufacture hours post-harvest
Long-term fatalities within 5 km	-0.000101	0.00225	0.00365
	(0.000150)	(0.00470)	(0.00434)
Female	-0.0201	0.273	-0.190
	(0.0138)	(0.568)	(0.698)
Age	0.00168	0.228**	-0.0757
	(0.00264)	(0.0988)	(0.110)
Age squared	-1.91e-05	-0.00243**	0.000457
	(2.76e-05)	(0.00104)	(0.00108)
Years of education	-0.00234	-0.0338	-0.0468
	(0.00150)	(0.0650)	(0.0517)
Age of household head	-0.00865***	-0.150	-0.137
	(0.00305)	(0.0997)	(0.123)
Age of household head squared	7.51e-05***	0.00139*	0.00121
	(2.64e-05)	(0.000795)	(0.00103)
Household's land size	5.83e-05	0.000890	-0.00361
	(7.58e-05)	(0.00382)	(0.00341)
Household's livestock value	5.37e-10	9.42e-08	2.09e-07*
	(4.13e-09)	(1.02e-07)	(1.19e-07)
Number of children in the household	0.00104	-0.0721	0.0439
	(0.00341)	(0.121)	(0.145)
Value of household's assets	-2.41e-08	8.64e-05*	4.55e-05
	(3.21e-06)	(4.97e-05)	(6.32e-05)
Household's distance to nearest market	0.000514	0.0176	0.0605
	(0.000924)	(0.0283)	(0.0372)
Annual Precipitation	1.99e-06	0.000478	0.00148
	(4.68e-05)	(0.00186)	(0.00215)
Constant	0.260*	-0.871	1.827
	(0.148)	(5.152)	(5.715)
Observations	16,296	16,296	16,296
R-squared	0.039	0.014	0.030

Notes: Each column represents a regression. Individual, state, and state-wave fixed effects are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 21: Long-term effects of conflicts on employment in services

	(1) Services	(2) Services hours post-planting	(3) Services hours post-harvest
Long-term fatalities within 5 km	1.57e-05	-0.0178*	-0.0130
	(8.21e-05)	(0.0106)	(0.00902)
Female	0.0193	2.654*	1.233
	(0.0305)	(1.592)	(1.337)
Age	0.0101**	0.927***	0.558**
	(0.00457)	(0.233)	(0.256)
Age squared	-0.000102**	-0.00819***	-0.00605**
	(4.95e-05)	(0.00259)	(0.00275)
Years of education	0.00321	0.0787	0.155
	(0.00203)	(0.127)	(0.127)
Age of household head	0.00238	0.116	-0.136
	(0.00511)	(0.264)	(0.273)
Age of household head squared	-4.86e-05	-0.00200	0.000405
	(4.61e-05)	(0.00221)	(0.00228)
Household's land size	-1.47e-05	-0.0138	-0.0208**
	(0.000484)	(0.0206)	(0.0104)
Household's livestock value	1.36e-08	6.70e-07	1.10e-06
	(1.33e-08)	(5.41e-07)	(8.24e-07)
Number of children in the household	0.00207	0.212	-0.0922
	(0.00532)	(0.310)	(0.334)
Value of household's assets	1.06e-06	0.000259	-0.000625
	(5.42e-06)	(0.000457)	(0.000383)
Household's distance to nearest market	-0.00282	0.135	0.139
	(0.00221)	(0.0925)	(0.142)
Annual Precipitation	-0.000207	0.00505	0.00322
	(0.000179)	(0.00787)	(0.00967)
Constant	0.816**	-7.438	3.088
	(0.392)	(18.42)	(21.80)
Observations	16,296	16,296	16,296
R-squared	0.027	0.035	0.029

Notes: Each column represents a regression. Individual, state, and state-wave fixed effects are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

4.5.3. Sensitivity analysis and edge effects

The two previous sections examined the effects of conflicts within 5 km of proximity to the households. However, people may also respond to conflict events that are relatively further away. This section examines how the effects of conflicts on the types of work and sectoral employment choices change with the increase in the radii of the conflict influence zone (20 km, 40 km, and LGA). The purpose of this analysis is to determine if better results come in as one expands the measurement of the size of the conflict impact zone. The results are presented in Tables 11 to 14. In these tables, panels A and B present the results using short and long-term measures of conflicts, respectively. Each panel presents the results using the four alternative measures of conflicts, namely the total number of fatalities recorded in buffers of radii 5, 20, and 40 km around the individuals' household, and the number of fatalities recorded in the LGA where the individual resides. Also note that, in order to focus on the sensitivity of the impact estimates, these tables do not report the coefficients of control variables included the regressions. The tables including the coefficients of control variables can be provided upon request.

Considering the types of work, Panel A of Table 22 shows that, in the short run, conflicts recorded within 40 km of individuals' household significantly reduce the probability of participating in family farm enterprises, confirming the impact found within 5 km. This suggests that the short run effect of conflict on the choice of having an agricultural livelihood is not constrained to the immediate conflict zone. However, the effect of conflicts on the probability of being employed outside the household is not significant at the 20 or 40 km radii and the LGA-level. These findings suggest that farm activities are also sensitive to distant conflicts, but non-farm activities are less sensitive, confirming the greater vulnerability of agriculture. Also, the effect on family non-farm enterprises is not statistically significant at the higher radii and LGA levels. Moreover, the effect on the diversification index remains non-significant at higher radii levels. But it is significant and negative when using the LGA-based measure. This result might imply that conflicts reduce the diversity in the types of activities available to people, thereby threatening their resilience to various covariate or idiosyncratic shocks and stressors. However, the difference between buffer-based and LGA-based effects might indicate the presence of edge effects affecting the LGA-based coefficients. In the long run, the significant effects detected on all the types of work within 5 km remain significant within 20 and 40 km (see Panel B of Table 22).

Table 23 presents the sensitivity analysis for the employment in agriculture. In the short run (Panel A), the negative effect of conflicts on the probability of being employed in agriculture remains significant within 20 km. Therefore, both family farm activities and agricultural jobs are sensitive to distant conflicts. In addition, the number of hours spent in an agricultural employment is significantly reduced in both planting and harvesting seasons. Hence, not only do people abandon farm activities, but those who remain in these activities tend to reduce their involvement. The finding of these effects during both planting and harvesting seasons suggests disruptions of all agricultural cycle’s phases. Hence, it provides evidence of disruptions of both inputs and outputs supply chains. The long-run results (Panel B) show that in contrast to the result considering a 5 km buffer, conflicts recorded within 20 km significantly reduce the probability of being employed in agriculture, which aligns with the short run results. In contrast, the positive effect on the time spent in agriculture becomes non-significant after increasing the buffer size or using the LGA-based measure.

Table 24 presents the sensitivity analysis for the employment in manufacturing. In the short run (Panel A), the analysis confirms the non-significance of the effects found within 5 km. The exception is a significant and positive effect on the time spent in employment in manufacturing during the agricultural harvesting season. The non-significance within 5 and 20 km and the significance within 40 km may indicate that most manufacturing activities are not located in areas directly exposed to conflicts. However, as people flee areas directly affected by conflicts, they may find refuge in more distant areas where manufacturing might provide them an alternative source of income to replace the farming activities they abandoned. This process takes time, so the short-term analysis might pick up the abandonment of farm activities but not necessarily the increased participation in the manufacturing activities. This is confirmed by the significant effects detected by the long-term analysis on the time spent in manufacturing activities when considering a 40 km radius (Panel B). The significance of this result in both the planting and harvesting seasons complements the previous result on short term effects on agricultural employment. Altogether, the results on the short-term effects on agricultural employment and the long-term effects on manufacturing show that people abandoned farm jobs and take an adjustment time to replace them by jobs in manufacturing. This adjustment time can be explained by the time required to move from areas directly exposed to conflicts to areas less exposed and the learning time needed before performing a manufacturing activity.

Table 25 presents the sensitivity analysis for the employment in services. In the short run (Panel A), the effects on the probability of being employed in this sector remains non-significant after increasing the buffers size to 20 or 40 km. However, it is positive and significant when using the LGA-based measure. This result, which might be due to edge effects, suggests that conflicts induce an entering movement in the services sector, which might also be linked to the abandonment of agricultural activities. The finding aligns with the search for off-farm employment observed as a response to conflicts, weather shocks, or idiosyncratic shocks (e.g., Branco and Féres, 2021; Cameron and Worswick, 2003; Cunguara et al., 2011; Mathenge and Tschirley, 2015). The negative and significant effect on the time spent employment in services detected within 5 km becomes non-significant as the radius of the influence zone increases. In the long run (Panel B), the only significant effects are observed within a radius of 40 km. These effects are negative and suggest that people tend to leave the employment in services over the time. This may be the result of the degradation of the business environment over time, which ends up by reducing the employment opportunities in the services sector. The negative effects can also be due to a diversification strategy: considering the risk associated with each source of income, individuals may reduce their time in services sector and increase the time allocated to other occupations or employment in other sectors. Another explanation is that more people entering the services sector can reduce the time spent in this sector by those already in it.

Overall, the results above confirm previous findings that people tend to diversify away from agriculture when exposed to conflicts (e.g., Branco and Féres, 2021; Cameron and Worswick, 2003; Cunguara et al., 2011; Fernández et al., 2014; Mathenge and Tschirley, 2015). They also show that the manufacturing sector can provide an alternative source of livelihood to people fleeing areas prone to conflicts, but an adjustment time is needed. They also suggest that the services sector can be an alternative but many service activities are sensitive to the disruptions experienced by the agricultural sector, probably because they provide agricultural related services.

Table 22: Sensitivity analysis for the impacts of conflicts on the types of work

	Dependent variables			
	Family farm enterprises	Family non-farm enterprises	Employment	Diversification
Panel A: Short-term conflict measurement method				
5 km around the individual's household	-0.000294***	4.88e-05	0.000140**	-0.000105
	(6.34e-05)	(7.76e-05)	(6.43e-05)	(0.000121)
20 km around the individual's household	-6.08e-05	4.17e-05	-7.45e-08	-1.91e-05
	(4.05e-05)	(3.67e-05)	(3.09e-05)	(6.30e-05)
40 km around the individual's household	-7.71e-05***	2.52e-05	1.00e-05	-4.19e-05
	(2.98e-05)	(2.44e-05)	(1.92e-05)	(4.41e-05)
LGA-based	-0.000198***	-2.05e-05	-3.64e-05	-0.000255***
	(6.00e-05)	(5.01e-05)	(3.45e-05)	(8.42e-05)
Panel B: Long-term conflict measurement method				
5 km around the individual's household	-0.000161***	6.68e-05**	8.80e-05***	-5.75e-06
	(2.19e-05)	(2.67e-05)	(2.50e-05)	(4.01e-05)
20 km around the individual's household	-0.000105***	5.32e-05***	3.12e-05**	-2.05e-05
	(1.74e-05)	(1.56e-05)	(1.32e-05)	(2.79e-05)
40 km around the individual's household	-6.49e-05***	3.18e-05***	2.29e-05**	-1.01e-05
	(1.34e-05)	(1.16e-05)	(9.57e-06)	(2.09e-05)
LGA-based	-0.000115***	6.57e-06	1.46e-05	-9.39e-05**
	(2.30e-05)	(2.04e-05)	(1.57e-05)	(3.77e-05)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 23: Sensitivity analysis for the effects of conflicts on employment in agriculture

	WorksInAgri	AgriHoursPP	AgriHoursPH
Panel A: Short-term conflict measurement method			
5 km around the individual's household	-0.000187**	0.00236	0.00660
	(8.88e-05)	(0.00467)	(0.00648)
20 km around the individual's household	-0.000123**	-0.00855**	-0.0109**
	(5.73e-05)	(0.00393)	(0.00505)
40 km around the individual's household	-1.89e-05	-0.00598*	-0.00345
	(5.30e-05)	(0.00350)	(0.00870)
LGA-based	-0.000146*	-0.0200***	-0.0162
	(8.85e-05)	(0.00706)	(0.00996)
Panel B: Long-term conflict measurement method			
5 km around the individual's household	-6.00e-05	0.00780**	0.00409
	(5.95e-05)	(0.00324)	(0.00325)
20 km around the individual's household	-0.000289***	0.000992	-0.00540
	(9.13e-05)	(0.00500)	(0.00484)
40 km around the individual's household	2.00e-06	0.00494	-0.00136
	(6.47e-05)	(0.00370)	(0.00313)
LGA-based	-0.000317*	-0.00654	-0.00357
	(0.000186)	(0.00653)	(0.00551)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 24: Sensitivity analysis for the effects of conflicts on employment in manufacturing

	WorksInManufacture	ManufactureHoursPP	ManufactureHoursPH
5 km around the individual's household	-0.000110	-0.00157	0.00628
	(0.000236)	(0.00862)	(0.00770)
20 km around the individual's household	6.80e-05	-0.000806	0.00471
	(7.53e-05)	(0.00207)	(0.00418)
40 km around the individual's household	4.24e-05	-6.16e-05	0.00714**
	(5.53e-05)	(0.00155)	(0.00290)
LGA-based	3.32e-05	0.000599	0.00546
	(6.97e-05)	(0.00243)	(0.00370)
5 km around the individual's household	-0.000101	0.00225	0.00365
	(0.000150)	(0.00470)	(0.00434)
20 km around the individual's household	3.15e-05	-0.000514	0.00558*
	(0.000104)	(0.00275)	(0.00298)
40 km around the individual's household	0.000111*	0.00415***	0.00423**
	(6.05e-05)	(0.00158)	(0.00195)
LGA-based	0.000189	0.00823*	0.0109***
	(0.000137)	(0.00453)	(0.00401)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 25: Sensitivity analysis for the effects of conflicts on employment in services

	WorksInServices	ServicesHoursPP	ServicesHoursPH
5 km around the individual's household	0.000152	-0.0364**	-0.0104
	(0.000123)	(0.0163)	(0.0153)
20 km around the individual's household	0.000153	-0.00572	0.00231
	(9.45e-05)	(0.00561)	(0.00757)
40 km around the individual's household	0.000125*	-0.00447	-0.00629
	(7.35e-05)	(0.00415)	(0.00623)
LGA-based	0.000279**	-0.00253	-0.000302
	(0.000126)	(0.00546)	(0.00879)
5 km around the individual's household	1.57e-05	-0.0178*	-0.0130
	(8.21e-05)	(0.0106)	(0.00902)
20 km around the individual's household	-6.91e-05	-0.00548	-0.00228
	(0.000100)	(0.00783)	(0.00586)
40 km around the individual's household	-0.000196***	-0.0116***	-0.00659
	(7.34e-05)	(0.00410)	(0.00542)
LGA-based	4.81e-06	-0.0137	-0.00709
	(0.000121)	(0.0101)	(0.0114)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

4.5.4. Heterogenous effects

This section examines how the results presented in the last three sections may differ based on gender and skill levels. The results are presented in appendix A3 (tables 47 to 54) and, as in the previous section, only include the coefficients associated with the measures of conflict. In these tables, Panels A and B present the results associated with the short and long run measures of conflict, respectively. Moreover, since the sensitivity of the results to alternative measurements approaches was already discussed in the previous section, this section only focuses only the differences between men and women or between skilled and nonskilled individuals.

4.5.4.1. Differences between men and women

Table 47 shows how the effects of conflicts on the choice of work (namely, family farm enterprises, family non-farm enterprises, or employment with others) differ between men and women. In the short run, conflicts significantly reduce the probability that both women and men participate in family farm enterprises. Similar results are found using the long run conflict measures. For family non-farm enterprises, there is no short run significant effect of conflict for women or men. However, in the long run, conflicts significantly increase the likelihood that men participate in family non-farm enterprises. Both short and long run results show that over time, men are gradually able to carry out non-farm enterprises, but women are less able to. This can limit the household resilience capacity. Turning to employment with others, the short run results indicate that conflicts significantly increase the probability of women having this type of work, while no significant effect is found for men. The long run results align with the short run results for women but find that the probability of men having an employment also significantly increases. Hence, as a result of conflict exposure, households immediately allocate women to employment with others while the reallocation of men to this type of work is more gradual. This might indicate that women have the skills required for the types of jobs available in the short run. Additionally, the impact on the diversification index is only significant for women in both short and long-term analyses. This result suggests potential disruptive effects of conflicts on women's occupations. The next paragraphs discuss how the impact of conflicts on sectoral employment choices (namely, employment in agriculture, manufacturing, or services) differ between women and men.

Table 48 shows how the effects of conflicts on employment in agriculture differ between men and women. In the short run, conflicts reduce the probability of men having an employment in agriculture. In addition, women's time in an agricultural employment is significantly reduced during the planting season. The long run conflict exposure significantly reduce the probability of men being employed in agriculture. In contrast to the short-term results, the long run exposure to conflicts significantly increases the time spent by women in agriculture during the harvesting season. In parallel, the time spent by men significantly increases but during the planting season. The increased involvement in agricultural jobs observed in the long run might be due to the loss of job opportunities in the non-agricultural sectors. In turn, this loss of job opportunities may result from the gradual degradation of the business environment.

Table 49 reports the results for the manufacturing sector. In the short run, conflicts significantly increases the time women spent in manufacturing during the agricultural harvesting season, but no significant effect is observed for men. This is in line with women's ability to occupy jobs available on the short run suggested earlier. The long run exposure to conflict significantly increases the time men spent in employment in manufacturing, in both the planting and harvesting seasons. For women, short and long run results are alike.

As shown in Table 50, in short run, conflicts significantly increase the probability of women being employed in services while no significant effect is found for men. Therefore, there is an entry movement of women in the services sector as a result of conflicts exposure. However, men significantly reduce their time spent in this sector during the planting season, while no significant effect is found for women. The long run exposure to conflicts significantly decrease both the probability that women work in services and the time men spent in this sector during the planting season.

Overall, these results point to a greater involvement by both men and women in nonagricultural sectors as a result of increased conflict exposure. Moreover, women are immediately (i.e., in the short run) reallocated to nonfarm activities and seem to have the skills necessary to perform this transition. The transition of men is more gradual.

4.5.4.2. Differences between low and high-skilled individuals

Table 51 shows how the effects of conflicts on the choice of type of work differ between low and high-skilled individuals. In the short run, conflicts significantly reduce the probability that low-skilled individuals participate in family farm enterprises but increase that of high-skilled individuals. The results based on the long run measures of conflicts are similar. For family non-farm enterprises, the effects remain insignificant in the short run after disaggregating by skill levels. However, the long run exposure to conflicts significantly increase the likelihood that low skilled individuals participate in family non-farm enterprises. The effects on employment also remain insignificant in the short run after disaggregating by skill levels. However, the long run exposure to conflicts significantly increase the probability of low skilled workers being employed. Moreover, conflicts significantly decrease the diversification index for low-skilled workers in the short-run, which has negative implications for their resilience capacity. However, the long run exposure to conflicts significantly increase the diversification index for high-skilled individuals. This reflects that their higher level of education provides them with some resilience capacity.

These results suggest that conflict mainly affects low-skilled individuals vis-à-vis their high-skilled counterparts. In the short run, they tend to lose some resilience capacity due to the disruption of their farm activities. They then respond to these adverse effects by moving away from family farm activities and substituting them with family non-farm enterprise or employment with others. Again, the insignificance of some results on the short run and their significance on the long run indicate that this substitution process takes an adjustment time.

Table 52 shows how the effects of conflicts on employment in agriculture differ between low and high-skilled individuals. In the short run, conflicts significantly reduce both the probability of low skilled individuals being employed in agriculture and the time they spent an agricultural employment. This result indicates that the low-skilled abandon not only their family farm enterprises as previously found, but also agricultural jobs. No significant effect is detected on the high-skilled in the short run. The long run exposure to conflict also reduce the probability of low-skilled individuals being employed in agriculture. However, the time spent by high-skilled individuals in employment in this sector significantly increases especially during the planting season. This result confirms the resilience capacity provided by education.

Table 53 focuses on employment in manufacturing. There is no significant effect in the short run after disaggregating by skill levels. However, the long run exposure to conflict significantly increase the time spent by low-skilled individuals in this sector. Table 54 focuses on employment in services. In the short run, conflicts significantly increase the probability of low-skilled individuals being employed in this sector, while no significant effect is found for the high-skilled. However, the long run exposure to conflict significantly reduce both the probability of low-skilled individuals being employed in this sector and the time they spent in it. However, it significantly increases the likelihood of high-skilled individuals being employed in this sector.

Hence, low-skilled individuals moved away from farm activities (including family farm enterprises and agricultural jobs) and tend to progressively substitute them with employment in other sectors. Over time, the manufacturing sector seem to provide them with alternative jobs, but their ability to find jobs in the services sector seems to be limited by some indirect effects of conflicts on the services sector. These indirect effects can be related to the degradation of the business environment or the many linkages between the services and agricultural sectors.

4.6. Robustness checks

The alternative approaches to measuring conflicts may serve as robustness checks for each other. As a reminder, these are short-term, long-term, buffer-based, and LGA-based measures of the number of fatalities. Moreover, the impacts of conflicts on the outcomes of interest can be estimated using the number of incidents as indicator of conflicts, instead of the number of fatalities. A number of previous papers used incidents as their primary indicator of conflict (e.g., Adelaja and George, 2019a, 2019b; Ekhator-Mobayode and Abebe Asfaw, 2019). In this article, the short and long-term effects of the number of incidents on the types of work and sectoral employment choices are estimated as additional robustness checks. The results are presented in tables 55 to 58. The estimated coefficients are broadly similar to those from the main regressions in terms of significance and signs.

Furthermore, individuals who left the sample between two consecutive waves can potentially pose an attrition bias problem. This issue is even more concerning if attrition is significantly determined by conflicts. To investigate this issue, Inverse Probability Weighting (IPW) is used to re-estimate the short and long-term effects of the number of fatalities on the types of work and sectoral employment choices, using the approach proposed by Wooldridge (2010). The four waves of the GHS are still used but the sample is restricted to the individuals who were observed since the first wave. In other words, individuals who entered the sample after the first wave are not included in this attrition analysis. In addition, an individual who left the sample is not allowed to reenter the sample in a subsequent wave. These restrictions allow to impose the assumption that attrition is an *absorbing state*.

The IPW method consists of three steps. The first is to estimate, in each wave $t \geq 2$, a binary response model for $P(s_{it} = 1|\boldsymbol{z}_{it}, s_{it-1} = 1)$ where s_{it} is a binary variable indicating that the individual i was observed (i.e., had not attrited) in wave t. $\boldsymbol{z}$ is the vector of the number of fatalities and values of control variables recorded in wave $t-1$. The binary response models are estimated using probit regressions and the standard errors are calculated to account for heteroskedasticity and serial correlation. The results, presented in Table 59, suggest that individual selection in the sample in waves 2 and 3 are significantly affected by the intensity of conflicts recorded in waves 1 and 2, respectively. However, the signs of the effects are counterintuitive, as they suggest that a higher intensity of conflicts in wave $t-1$ increases the probability of that the individual was observed in wave t. Moreover, individual selection in wave 4 is not significantly affected by the intensity of conflicts recorded in wave 3. Hence, these results provide weak evidence that the individuals leave the sample because of conflicts. The results of the probit regressions are used to estimate the fitted probabilities $\hat{\pi}_{it}$, which represent the estimated probability that the individual i observed in wave $t-1$ was also observed in wave t, after controlling for $\boldsymbol{z}$. The second step of the IPW method consists of calculating, in each wave $t \geq 2$, the probabilities $\hat{p}_{it} = \hat{\pi}_{it}\hat{\pi}_{i,t-1} \dots \hat{\pi}_{i2}, t = 2,3,4$. In the last step, the main regressions are estimated using via pooled OLS using the inverse of $\hat{p}_{it}$ as individual weights. Again, the standard errors are calculated to account for heteroskedasticity and serial correlation. The results are presented in tables 60 to 63 and do not substantially differ from the main results in terms of significance and signs of the coefficients.

4.7. Conclusion and policy implications

The spread of conflicts and their mounting socioeconomic costs in developing countries has stimulated interest in urgent measures to reduce the vulnerability of populations exposed to these violent shocks and improve their resilience capacities in the short and long runs. A key component of individuals and households' vulnerability and resilience is the mix of coping strategies that they mobilize to cushion the adverse impacts of shocks. This study provides evidence for two types of labor reallocation strategies used as coping strategies. First, individuals can reallocate labor between types of work, namely family farm enterprises, family non-farm enterprises, and employment with others. They can also change their sectoral employment choices, namely choosing between employment in agriculture, manufacturing, or services. These labor reallocation effects have numerous implications for individuals or households' vulnerability and resilience to covariate and idiosyncratic shocks and stressors (e.g., droughts, desertification, climate change, etc.), sectoral productivities, and subsequently for the design of appropriate policy responses or support measures.

The abandonment of agricultural activities is a potential threat to food security not only for the farmers themselves, but also for those who depend on the markets supplied by these farmers. A substantial portion of agricultural households mainly depend on agriculture for their subsistence and a sudden disruption of their ability to perform this activity is detrimental for both their income and food security since their self-consume part or all their production. Indirect effects on non-agricultural households can occur through a short-term rise in the prices due to a negative supply shock. In addition, the abandonment of farm activities can reduce the productivity of the agricultural sector especially if there is a relatively higher abandonment by higher skilled agricultural workers. This effect on productivity can remain on the long run if these workers do not return after the end of conflicts, implying a detrimental change in the composition of the agricultural labor force. The abandonment of farm activities can also cause a loss of land tenure security which is a determinant of agricultural investment and productivity. Reduced agricultural investment will decrease the agricultural growth in the short-run and potentially in the long-run if appropriate policy responses are not undertaken. Hence, policy support measures for populations exposed to conflicts must consider protecting incomes and food security, promoting the return of both qualified and non-qualified agricultural workers, and developing context-specific measures for securing land tenure.

The findings also suggest that farm activities tend to be replaced by employment in other sectors. That is, individuals can withstand the violent shocks by finding employment with other people in the non-agricultural sectors. Hence, an essential determinant of this coping strategy is the individual s' ability to transition from one activity to another. This ability, in turn, depends on the individuals' human capital and the flexibility of the labor market, two areas where policy makers also need to focus their attention. Note also that a sudden movement of labor from farm activities to other activities can not only reduce the farm production but potentially reduce the productivity of other activities receiving the sudden flow of labor. This is due to the short run decreasing marginal return of labor, let alone the fact that incoming workers are not necessarily qualified for the types of employment with others. In the absence of a flexible job market this outflow of labor out of the agricultural sector will raise the rates of underemployment and unemployment that are already relatively high. Additionally, these labor reallocations tend to be accompanied by an overall reduction in the degree of diversification of individuals' activities, which is a direct threat to their resilience capacity, limiting their ability to withstand other covariate and idiosyncratic shocks.

Furthermore, the findings suggest different effects across gender and skill levels. Both women and men increase their involvement in nonagricultural sectors as a result of increased exposure to conflict. While women are immediately reallocated to nonfarm activities and seem to have the skills necessary to perform this transition, the transition of men is more gradual. From the skill levels perspective, the findings suggest that low skilled individuals are more vulnerable to conflicts' adverse effects. Hence, better access to labor markets and improved access to education should be considered in resilience building strategies. An improved ability to work in activities that are less disrupted by the climate of fear and uncertainty caused by conflicts will improve the households' ability to withstand the disruptive effects of conflicts. Improving individuals' education will equip them with the ability to adapt to the change in the economic environment caused by conflicts. Following the conceptual view of resilience developed by development stakeholders such as the Food and Agriculture Organization or the United States Agency for International Development, these results suggest that improving access to education will provide individuals with the adaptive capacity required to withstand the effects of conflicts.

The findings of significant impacts occurring in all agricultural seasons have implications for the development of agricultural value chains. From a value chain perspective, these results indicate that the supply chains linked to planting activities (e.g., seeds and fertilizers' supply chains) and those linked to harvesting activities are all disrupted by conflicts. Consequently, the incomes of those working in these supply chains may also be at risk. Since the upgrading of agricultural value chains is at the core of economic development strategies in developing countries, policy measures aiming at protecting these supply chains should probably be considered in developing mitigation measures to curtail the direct impact on the agricultural production cycle.

In addition, because the long run measures of conflicts capture the vulnerability to conflicts, the business environment, and the range of economic opportunities available, the findings of this study also support the hypothesis that economic development is an appropriate long term solution to conflict. The last key implication of this analysis is of methodological nature. Testing the presence of edge effects in conflicts analysis reveals that these effects are present especially when using LGA-based measures of conflicts. While individuals located near an LGAs' border are significantly affected by events occurring outside the LGA, measures reflecting greater spheres of conflict influence can pick up these effects while LGA-based measures do not because they ignore what happened outside the individuals' LGA. Hence, more encompassing measures of conflict which take into consideration appropriate measures of the spheres of influence are recommended to future studies.

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CHAPTER 5. CONCLUSION AND POLICY IMPLICATIONS

Terrorist attacks, epidemics, and droughts represent elements of the shocks that threaten the survival and livelihoods of individuals, households, and communities in Sub-Saharan Africa (SSA). These shocks can directly affect development outcomes such as income, food security, health, and education. They can also alter the drivers of the long-term economic transformation process such as productivity and labor allocation. Due to their increasing spread, frequency, and socioeconomic costs, resilience building has rapidly become a critical aspect of policy responses and development strategies. Resilience building is the primary means of preventing economic agents from experiencing a permanent decline in well-being and preserving the progress already made towards the Sustainable Development Goals. Resilience building is also about preventing indicators of socioeconomic well-being from deviating from their long-term positive trends. Designing or improving policy responses or development strategies that promote resilience requires a sound understanding of the shock-resilience-development nexus. In this vein, this thesis seeks to explain the mechanisms by which some of the most prevalent shocks in SSA affect the well-being of the population and to explore the role of resilience factors. The combination of micro and macro scales analyses, short and long run perspectives, and relevant indicators of both well-being, development, and resilience provides significant contributions to the literature and valuable policy implications.

Focusing on the COVID-19 context, the first essay nuances the convention that this dual health-policy shock is associated with widespread harmful socioeconomic effects by explaining how certain resilience factors enabled some agricultural households to mitigate the negative effects and potentially benefit from the shock. Essay 1 also identifies some factors that instead increases household vulnerability to this shock. These resilience or vulnerability factors include the land size, wealth level, and the degrees of income diversification, involvement in processing activities, and reliance on hired labor. These findings suggest that developing processing capacity could help prepare these households to withstand similar shocks in the future. Developing the processing capacity involves providing appropriate training and addressing their lack of financial capital, among other necessary measures. As household diversification is a factor in resilience capacity building, creating the conditions for households to diversify their income sources should be considered in resilience building policies and strategies. This essay also provides additional explanation of the direct effects of policy responses to shocks on agriculture and stresses the need to carefully consider the uniqueness of the agricultural sector in designing policy responses or complementary support measures. For instance, the greater vulnerability of larger farmers to stay at home orders compared to smallholder farmers suggests the design of more targeted policy responses or the provision of targeted support measures for those who are more likely to be negatively affected by the policy response.

The second essay examines how conflict and drought undermine the processes of agricultural and economic transformation, considering productivity as one of the best available indicator of these processes. Since productivity gains are central in these processes, a shock to productivity can deviate these transformations from their long-term trajectory, especially if the effects of these shocks on productivity persist beyond the short term. Therefore, policies and strategies to prevent sustained deviations of productivity levels from their normal growth trajectories should also prevent sustained deviations of agricultural and economic transformations from their normal trajectories. The empirical analysis suggests that conflicts do not permanently cause deviations in agricultural total factor productivity from its long-term trajectory, but leads to long-term disruption in the uses and quality of machinery and fertilizer. In contrast, droughts persistently disrupt the uses and quality of land, labor, livestock, machinery, and fertilizer and thus the structure of agricultural production. Moreover, the structure of agricultural production is found to be more resilient to conflicts than to drought. These results provide additional support for the investment in drought-resilient technologies, including irrigation technologies and the development of climate-resilient crop varieties. For conflict-prone areas, the results underscore the importance of promoting the return of low- and high-skilled workers in the aftermath of conflicts and the need to develop context-specific mechanisms for protecting land tenure security.

Essay 2 also shows the extent to which the effects of long-term stressors such as climate change can be underestimated: by exacerbating the frequency and severity of shocks such as conflicts and droughts, climate change might have more disruptive effect on development than anticipated. Therefore, at the very least, these results call for intensifying the policy debate (e.g., ongoing debates on climate adaptation, renewable energy and energy finance in Africa, and the United Nations Climate Change Conference (COP) negotiations) and taking appropriate measures to bend the curve of climate change and accelerate climate adaptation. In these debates, the loss and damages typically associated with climate change include sea level rise, rising temperatures, ocean acidification, glacial retreat, salinization, desertification, and the degradation of land, forest, and biodiversity (UNFCC, 2022b). Essay 2 shows that these loss and damages should be extended to the long run productivity losses and the opportunity costs involved in the slowdown of the process of agricultural transformation. As the United Nations Climate Change Conference COP27 closed with the agreement to provide loss and damage funding to vulnerable countries prone to climate disasters (UNFCC, 2022a), loss and damages occurring through productivity losses and opportunity cost of the slowdown of the process of agricultural transformation should be quantified to provide the appropriate funding to each vulnerable country. This cost assessment could be conducted by the Warsaw International Mechanism for Loss and Damage established by the COP19 (see UNFCC, 2022c). Furthermore, these efforts should be fed by additional research, especially on the links between climate change, shocks, and development outcomes. Specifically, empirical results are needed on the impacts of different shocks on energy consumption, greenhouse gas emissions, energy finance, and climate adaptation. These impacts should also be quantified for different scenarios of climate change such as the Representative Concentration Pathways (RCPs) identified by the Intergovernmental Panel on Climate Change.

The third essay seeks to examine how conflict disrupts individuals' labor allocation choices. Preserving the ability of individuals exposed to this type of shock to reallocate their labor optimally is important because the diversity of income sources is a key resilience factor and labor reallocations are a widespread coping strategy in the developing world. The results of this essay confirm the abandonment of agricultural activities which tend to be replaced by employment in other sectors, but they also highlight that the effects may differ by gender and skill level. Women labor appears to be immediately reallocated to non-farm activities and they seem to have the skills necessary to make this transition, while men's transition is more gradual. In addition, the low-skilled are found to be more vulnerable to the adverse effects of conflicts. Furthermore, the significant effects observed during both planting and harvesting seasons suggest disruptive effects of conflict on supply chains related to both planting and harvesting activities.

It should also be noted that the abandonment of agricultural activities in conflict-prone areas directly affects the food security of farmers, and indirectly that of the people who depend on the markets supplied by these farmers. Hence, in addition to policies and strategies aimed at mitigating conflict, those aimed at reducing the barriers to labor markets, improving access to education, promoting the return of low- and high-skilled workers, protecting land tenure security and supply chains could improve the resilience capacity of populations affected by conflict. Additionally, the indirect effects of conflicts occurring through market dependency and supply chains must be considered in the design measures to support populations affected by conflict.

The combination of labor reallocation effects detected at the micro level and the sectoral productivity changes at the macro level suggests that the shocks evaluated in these dissertation can alter the process of structural transformation, which is a condition for long-term development. Although structural transformation is a long-term process, the protracted nature of many of these shocks indicate that they can have an impact on structural transformation. For instance, the COVID-19 pandemic already lasted three years and some researchers point out that similar pandemics are more likely in the near future. The Boko Haram insurgency, which began in 2009, has already lasted thirteen years. The flight of human capital induced by such long-lasting conflicts may cause induce irreversible changes in the composition of the labor, thereby reducing productivity gains on the short and long runs.

Finally, it should be noted that this dissertation focuses on resilience capacities that can be developed over the medium to long term. For example, skill levels take years to develop, and processing capabilities require years of training and the development of complementary markets for inputs and outputs. However, these shocks also require effective short-term policy responses, such as the use of grain reserves observed in some African countries during the pandemic and targeted cash transfers. Empirical analyses of the effectiveness of such policy responses remain a gap in the literature. Further research is also needed on the long-term effects of the policy responses to shocks and the resilience factors associated with non-farm activities. Finally, future researchers could consider the use of qualitative date (interview, survey, etc.) to ground-truth or corroborate the findings of this dissertation. They could also extend the analysis to other segments of the food value chains especially agricultural inputs, foods, and markets.

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APPENDIX A1: APPENDICES FOR ESSAY 1

Table 26: Variables' description for essay 1

Variable(s)	Definition(s) / Question(s) and codes	Source
	Compared to this time last year (August 2019), is your household's income from household farming, livestock, or fishing Increased? Stayed the same? Decreased?	NLPS
IIF	Farm income increased (= 1 if farm income increased, 0 otherwise)	
IDF	Farm income decreased (= 1 if farm income decreased, 0 otherwise)	
	Compared to this time last year (august 2019), is your household's income from Non-Farm Family Business (NFFB) increased? stayed the same? decreased?	NLPS
IIN	NFFB income increased (= 1 if NFFB income increased, 0 otherwise)	
IDN	NFFB income decreased (= 1 if NFFB income decreased, 0 otherwise)	
	Compared to this time last year (august 2019), is your household's income from Non-Farm Family Business (Job) increased? stayed the same? decreased?	NLPS
IIJ	Job income increased (= 1 if Job income increased, 0 otherwise)	
IDJ	Job income decreased (= 1 if Job income decreased, 0 otherwise)	
SAH	Advised citizens to stay at home	NLPS
AGA	Advised to avoid gatherings	NLPS
ITR	Restricted travel within country/area	NLPS
ETR	Restricted international travel	NLPS
SCC	Closure of schools and universities	NLPS
CFL	Curfew/lockdown	NLPS
NEBC	Closure of non-essential businesses	NLPS
SEN	Sensitization/public awareness	NLPS
ISC	Established isolation centers	NLPS
PDI	Disinfection of public places	NLPS
HiredShare	Proportion of hours worked by hired labor	GHS
ProcessedShare	Share of crops processed and sold	GHS

Table 26 (cont'd)

LivestockValue	Value of the livestock (Naira)	GHS
AssetsValue	Value of assets (Naira)	GHS
SafetyNet	Recipient of safety nets (1 = yes, 0 = No)	GHS
HHindex	Normalized Herfindahl–Hirschman Index of income diversification	GHS
Land	Total land size owned (ha)	Harmonized
Remittances	Received Remittance (1 = yes, 0 = no)	Harmonized
rural	Rural (1 = yes, 0 = no)	Harmonized
toilet	Access to improved toilet (1 = yes, 0 = no)	Harmonized
water	Access to improved drinking water source (1 = yes, 0 = no)	Harmonized
elect	Connection to electricity (1 = yes, 0 = no)	Harmonized
tv	Ownership of television (1 = yes, 0 = no)	Harmonized
radio	Ownership of radio (1 = yes, 0 = no)	Harmonized
mphone	Ownership of mobile phone (1 = yes, 0 = no)	Harmonized
internet	Access to Internet (1 = yes, 0 = no)	Harmonized
Quintile	Consumption quintile (1=Poorest, 2=Poorer, 3=Middle, 4=Richer, 5=Richest)	Harmonized
WorkingAdults	% of working adults working	Harmonized
nfe	Ownership of non-farm family enterprise (1 = yes, 0 = no)	Harmonized
NbCrops	Number of crops cultivated	Harmonized
CashCrop	Cash crop cultivation (1 = yes, 0 = no)	Harmonized
Hired	Use of hired labor (1 = yes, 0 = no)	Harmonized
ExchangeLabor	Use of exchange and/or free labor (1 = yes, 0 = no)	Harmonized
SellCrop	Sale of crop (1 = yes, 0 = no)	Harmonized
ProcessSellCrop	Sale of processed crop (1 = yes, 0 = no)	Harmonized
SellUnprocessed	Sale of unprocessed crop (1 = yes, 0 = no)	Harmonized

Table 26 (cont'd)

LivestockOwnership	Ownership of livestock (1 = yes, 0 = no)	Harmonized
FoodInsecurity	Probability of being moderately/ severely food insecure >= 50%	Harmonized
Adults	Number of adults in the household, computed based on the standard FAO scale	Harmonized

Table 27: Means comparison for SAH

Variable	Mean control group	SD of control group	Mean treatment group	SD treatment group	diff	SE diff	p-value
rural	0.17	0.40	0.20	0.40	0.03	0.03	0.28
toilet	0.58	0.49	0.58	0.49	0.00	0.04	0.97
water	0.18	0.37	0.16	0.37	-0.02	0.03	0.50
elect	0.54	0.50	0.50	0.50	-0.04	0.04	0.31
tv	0.50	0.49	0.42	0.49	-0.08	0.04	0.03
radio	0.56	0.49	0.58	0.49	0.03	0.04	0.47
mphone	0.84	0.40	0.80	0.40	-0.04	0.03	0.16
internet	0.35	0.49	0.38	0.49	0.04	0.03	0.30
Land	0.87	1.58	1.15	1.58	0.28	0.11	0.01
Quintile	2.92	1.32	2.68	1.32	-0.24	0.09	0.01
Remittances	0.32	0.46	0.31	0.46	-0.01	0.03	0.66
WorkingAdults	68.10	32.60	64.55	32.60	-3.55	2.36	0.13
nfe	0.60	0.49	0.59	0.49	-0.01	0.03	0.77
NbCrops	5.09	3.26	4.63	3.26	-0.46	0.23	0.04
CashCrop	0.26	0.45	0.28	0.45	0.02	0.03	0.61
Hired	0.87	0.35	0.86	0.35	-0.01	0.02	0.80
ExchangeLabor	0.44	0.49	0.42	0.49	-0.02	0.04	0.66
SellCrop	0.73	0.46	0.69	0.46	-0.03	0.03	0.29
ProcessSellCrop	0.07	0.24	0.06	0.24	-0.01	0.02	0.58
SellUnprocessed	0.68	0.47	0.66	0.47	-0.02	0.03	0.65
LivestockOwnership	0.60	0.48	0.63	0.48	0.02	0.03	0.49
FoodInsecurity	0.38	0.43	0.25	0.43	-0.13	0.03	0.00
Adults	4.97	2.92	5.59	2.92	0.62	0.21	0.00
HiredShare	0.33	0.28	0.33	0.28	0.00	0.02	0.82
ProcessedShare	0.04	0.14	0.03	0.14	-0.01	0.01	0.34
LivestockValue	129011	439042	173148	439042	44136	30783	0.15
AssetsValue	267175	5558726	465974	5558726	198799	337726	0.56
education	9.55	5.02	9.79	5.02	0.24	0.39	0.53
NFEshare	0.49	0.43	0.48	0.43	-0.01	0.03	0.64
SafetyNet	0.09	0.35	0.14	0.35	0.05	0.02	0.03
HHindex	0.74	0.25	0.73	0.25	-0.01	0.02	0.46

Table 28: Means comparison for AGA

Variable	Mean control group	SD of control group	Mean treatment group	SD treatment group	diff	SE diff	p-value
rural	0.22	0.38	0.18	0.38	-0.04	0.03	0.11
toilet	0.60	0.50	0.57	0.50	-0.04	0.03	0.30
water	0.21	0.35	0.14	0.35	-0.06	0.03	0.01
elect	0.58	0.50	0.48	0.50	-0.11	0.03	0.00
tv	0.54	0.49	0.40	0.49	-0.13	0.03	0.00
radio	0.52	0.49	0.60	0.49	0.08	0.03	0.02
mphone	0.83	0.40	0.80	0.40	-0.03	0.03	0.26
internet	0.40	0.48	0.36	0.48	-0.04	0.03	0.22
Land	0.80	1.62	1.20	1.62	0.40	0.10	0.00
Quintile	3.00	1.31	2.63	1.31	-0.37	0.09	0.00
Remittances	0.36	0.45	0.29	0.45	-0.07	0.03	0.02
WorkingAdults	68.99	33.01	63.91	33.01	-5.08	2.25	0.02
nfe	0.59	0.49	0.60	0.49	0.00	0.03	0.95
NbCrops	5.03	3.18	4.62	3.18	-0.42	0.22	0.06
CashCrop	0.24	0.46	0.29	0.46	0.05	0.03	0.07
Hired	0.86	0.34	0.86	0.34	0.00	0.02	0.92
ExchangeLabor	0.37	0.50	0.45	0.50	0.08	0.03	0.02
SellCrop	0.71	0.46	0.70	0.46	-0.01	0.03	0.82
ProcessSellCrop	0.08	0.24	0.06	0.24	-0.02	0.02	0.18
SellUnprocessed	0.68	0.47	0.67	0.47	-0.01	0.03	0.74
LivestockOwnership	0.52	0.47	0.67	0.47	0.15	0.03	0.00
FoodInsecurity	0.34	0.44	0.26	0.44	-0.08	0.03	0.01
Adults	4.83	3.01	5.70	3.01	0.88	0.20	0.00
HiredShare	0.31	0.28	0.34	0.28	0.03	0.02	0.12
ProcessedShare	0.04	0.15	0.03	0.15	-0.01	0.01	0.30
LivestockValue	97766	487327	190465	487327	92698	29287	0.00
AssetsValue	261922	5742652	481626	5742652	219704	322555	0.50
education	10.15	5.17	9.53	5.17	-0.62	0.37	0.10
NFEshare	0.46	0.43	0.49	0.43	0.03	0.03	0.38
SafetyNet	0.09	0.35	0.14	0.35	0.05	0.02	0.02
HHindex	0.73	0.24	0.73	0.24	0.00	0.02	0.88

Table 29: Means comparison for ITR

Variable	Mean control group	SD of control group	Mean treatment group	SD treatment group	diff	SE diff	p-value
rural	0.20	0.39	0.18	0.39	-0.01	0.03	0.63
toilet	0.58	0.49	0.58	0.49	0.00	0.03	0.91
water	0.17	0.36	0.15	0.36	-0.02	0.02	0.47
elect	0.55	0.50	0.44	0.50	-0.11	0.03	0.00
tv	0.50	0.48	0.35	0.48	-0.14	0.03	0.00
radio	0.55	0.49	0.62	0.49	0.07	0.03	0.03
mphone	0.83	0.43	0.76	0.43	-0.07	0.03	0.01
internet	0.37	0.48	0.37	0.48	0.00	0.03	0.90
Land	0.89	1.83	1.42	1.83	0.53	0.10	0.00
Quintile	2.85	1.32	2.54	1.32	-0.31	0.09	0.00
Remittances	0.33	0.45	0.28	0.45	-0.05	0.03	0.09
WorkingAdults	66.37	32.54	63.93	32.54	-2.44	2.19	0.27
nfe	0.60	0.49	0.58	0.49	-0.02	0.03	0.55
NbCrops	4.83	3.37	4.59	3.37	-0.24	0.21	0.26
CashCrop	0.25	0.47	0.32	0.47	0.07	0.03	0.01
Hired	0.86	0.34	0.87	0.34	0.01	0.02	0.62
ExchangeLabor	0.40	0.50	0.48	0.50	0.08	0.03	0.02
SellCrop	0.71	0.46	0.69	0.46	-0.01	0.03	0.62
ProcessSellCrop	0.07	0.25	0.06	0.25	0.00	0.02	0.88
SellUnprocessed	0.67	0.47	0.66	0.47	-0.01	0.03	0.84
LivestockOwnership	0.59	0.47	0.68	0.47	0.10	0.03	0.00
FoodInsecurity	0.31	0.43	0.24	0.43	-0.07	0.03	0.02
Adults	5.12	3.08	6.00	3.08	0.88	0.19	0.00
HiredShare	0.32	0.29	0.36	0.29	0.05	0.02	0.01
ProcessedShare	0.04	0.13	0.03	0.13	-0.01	0.01	0.48
LivestockValue	131786	536528	215528	536528	83742	28512	0.00
AssetsValue	478843	809283	289948	809283	-188896	313817	0.55
education	9.82	5.42	9.55	5.42	-0.28	0.36	0.44
NFEshare	0.48	0.43	0.47	0.43	-0.01	0.03	0.73
SafetyNet	0.12	0.34	0.13	0.34	0.01	0.02	0.59
HHindex	0.74	0.24	0.72	0.24	-0.01	0.02	0.38

Table 30: Means comparison for SCC

Variable	Mean control group	SD of control group	Mean treatment group	SD treatment group	diff	SE diff	p-value
rural	0.21	0.37	0.16	0.37	-0.05	0.03	0.06
toilet	0.56	0.49	0.61	0.49	0.05	0.03	0.09
water	0.19	0.33	0.12	0.33	-0.07	0.02	0.01
elect	0.58	0.49	0.40	0.49	-0.17	0.03	0.00
tv	0.52	0.47	0.31	0.47	-0.21	0.03	0.00
radio	0.55	0.49	0.61	0.49	0.06	0.03	0.09
mphone	0.85	0.43	0.75	0.43	-0.10	0.03	0.00
internet	0.39	0.48	0.35	0.48	-0.04	0.03	0.25
Land	0.86	1.73	1.44	1.73	0.58	0.10	0.00
Quintile	2.97	1.27	2.36	1.27	-0.61	0.08	0.00
Remittances	0.34	0.44	0.26	0.44	-0.08	0.03	0.01
WorkingAdults	69.39	32.81	59.16	32.81	-10.23	2.13	0.00
nfe	0.57	0.48	0.64	0.48	0.07	0.03	0.04
NbCrops	5.01	3.05	4.31	3.05	-0.70	0.21	0.00
CashCrop	0.24	0.47	0.33	0.47	0.09	0.03	0.00
Hired	0.87	0.35	0.86	0.35	-0.01	0.02	0.81
ExchangeLabor	0.37	0.50	0.51	0.50	0.14	0.03	0.00
SellCrop	0.74	0.48	0.64	0.48	-0.10	0.03	0.00
ProcessSellCrop	0.07	0.22	0.05	0.22	-0.02	0.02	0.18
SellUnprocessed	0.70	0.49	0.61	0.49	-0.09	0.03	0.00
LivestockOwnership	0.57	0.46	0.70	0.46	0.13	0.03	0.00
FoodInsecurity	0.34	0.40	0.19	0.40	-0.14	0.03	0.00
Adults	4.79	3.06	6.48	3.06	1.69	0.19	0.00
HiredShare	0.33	0.29	0.34	0.29	0.01	0.02	0.60
ProcessedShare	0.04	0.13	0.03	0.13	-0.01	0.01	0.17
LivestockValue	98374	584733	266209	584733	167835	27750	0.00
AssetsValue	498336	778182	268901	778182	-229436	309584	0.46
education	10.16	5.50	9.01	5.50	-1.15	0.35	0.00
NFEshare	0.45	0.43	0.53	0.43	0.08	0.03	0.00
SafetyNet	0.10	0.37	0.16	0.37	0.06	0.02	0.01
HHindex	0.73	0.23	0.74	0.23	0.01	0.02	0.60

Table 31: Means comparison for CFL

Variable	Mean control group	SD of control group	Mean treatment group	SD treatment group	diff	SE diff	p-value
rural	0.18	0.41	0.21	0.41	0.03	0.02	0.17
toilet	0.56	0.49	0.60	0.49	0.04	0.03	0.17
water	0.16	0.38	0.17	0.38	0.01	0.02	0.64
elect	0.54	0.50	0.47	0.50	-0.07	0.03	0.03
tv	0.47	0.49	0.42	0.49	-0.04	0.03	0.16
radio	0.58	0.50	0.56	0.50	-0.02	0.03	0.55
mphone	0.83	0.42	0.78	0.42	-0.06	0.02	0.02
internet	0.37	0.48	0.38	0.48	0.01	0.03	0.82
Land	0.99	1.58	1.19	1.58	0.20	0.09	0.03
Quintile	2.86	1.26	2.59	1.26	-0.28	0.08	0.00
Remittances	0.32	0.45	0.29	0.45	-0.03	0.03	0.23
WorkingAdults	67.77	33.31	62.59	33.31	-5.18	2.10	0.01
nfe	0.59	0.49	0.61	0.49	0.02	0.03	0.46
NbCrops	5.11	3.06	4.29	3.06	-0.82	0.20	0.00
CashCrop	0.26	0.46	0.29	0.46	0.03	0.03	0.34
Hired	0.85	0.32	0.88	0.32	0.03	0.02	0.12
ExchangeLabor	0.42	0.50	0.44	0.50	0.02	0.03	0.47
SellCrop	0.72	0.47	0.68	0.47	-0.04	0.03	0.18
ProcessSellCrop	0.06	0.26	0.07	0.26	0.01	0.02	0.67
SellUnprocessed	0.69	0.48	0.65	0.48	-0.04	0.03	0.19
LivestockOwnership	0.59	0.47	0.66	0.47	0.07	0.03	0.02
FoodInsecurity	0.34	0.40	0.21	0.40	-0.14	0.03	0.00
Adults	5.00	2.90	5.97	2.90	0.97	0.19	0.00
HiredShare	0.33	0.27	0.34	0.27	0.01	0.02	0.44
ProcessedShare	0.03	0.15	0.03	0.15	0.00	0.01	0.96
LivestockValue	131658	501476	199210	501476	67552	27477	0.01
AssetsValue	494518	781882	307021	781882	-187497	302045	0.53
education	9.75	5.21	9.69	5.21	-0.06	0.35	0.86
NFEshare	0.47	0.43	0.49	0.43	0.02	0.03	0.40
SafetyNet	0.11	0.36	0.15	0.36	0.04	0.02	0.04
HHindex	0.73	0.24	0.73	0.24	0.00	0.02	0.89

Table 32: Means comparison for NEBC

Variable	Mean control group	SD of control group	Mean treatment group	SD treatment group	diff	SE diff	p-value
rural	0.20	0.37	0.16	0.37	-0.04	0.03	0.12
toilet	0.57	0.49	0.61	0.49	0.04	0.03	0.24
water	0.18	0.34	0.13	0.34	-0.05	0.02	0.05
elect	0.56	0.49	0.42	0.49	-0.14	0.03	0.00
tv	0.48	0.48	0.37	0.48	-0.11	0.03	0.00
radio	0.56	0.49	0.60	0.49	0.04	0.03	0.24
mphone	0.84	0.43	0.75	0.43	-0.08	0.03	0.00
internet	0.38	0.48	0.36	0.48	-0.01	0.03	0.71
Land	0.93	1.75	1.38	1.75	0.45	0.10	0.00
Quintile	2.85	1.34	2.53	1.34	-0.32	0.09	0.00
Remittances	0.32	0.45	0.28	0.45	-0.05	0.03	0.15
WorkingAdults	68.61	33.68	59.27	33.68	-9.34	2.20	0.00
nfe	0.58	0.49	0.62	0.49	0.04	0.03	0.20
NbCrops	4.98	2.90	4.28	2.90	-0.70	0.22	0.00
CashCrop	0.25	0.47	0.32	0.47	0.07	0.03	0.03
Hired	0.85	0.32	0.88	0.32	0.03	0.02	0.23
ExchangeLabor	0.39	0.50	0.50	0.50	0.11	0.03	0.00
SellCrop	0.73	0.48	0.65	0.48	-0.09	0.03	0.01
ProcessSellCrop	0.06	0.26	0.07	0.26	0.00	0.02	0.77
SellUnprocessed	0.69	0.49	0.62	0.49	-0.08	0.03	0.02
LivestockOwnership	0.61	0.48	0.65	0.48	0.05	0.03	0.16
FoodInsecurity	0.32	0.41	0.22	0.41	-0.10	0.03	0.00
Adults	5.13	2.86	6.02	2.86	0.89	0.20	0.00
HiredShare	0.32	0.28	0.36	0.28	0.04	0.02	0.06
ProcessedShare	0.03	0.15	0.04	0.15	0.00	0.01	0.88
LivestockValue	122816	580867	240329	580867	117513	28910	0.00
AssetsValue	471798	827656	290133	827656	-181665	319444	0.57
education	9.78	5.53	9.60	5.53	-0.18	0.37	0.62
NFEshare	0.46	0.43	0.51	0.43	0.05	0.03	0.11
SafetyNet	0.11	0.36	0.16	0.36	0.05	0.02	0.03
HHindex	0.73	0.23	0.74	0.23	0.01	0.02	0.72

Table 33: Average effects of containment measures on the likelihood that the income from non-farm family business increased

	(1) IIN	(2) IIN	(3) IIN	(4) IIN	(5) IIN	(6) IIN	(7) IIN
SAH	0.0271	0.0453					
	(0.0518)	(0.0503)					
AGA	-0.0765		-0.0277				
	(0.0513)		(0.0497)				
ITR	0.0314			0.0637			
	(0.0514)			(0.0486)			
CFL	-0.0312				0.0273		
	(0.0452)				(0.0450)		
NEBC	0.0650					0.0905*	
	(0.0586)					(0.0521)	
SCC	0.110*						0.126**
	(0.0642)						(0.0552)
Observations	665	665	665	665	665	665	665
Pseudo R2	0.111	0.094	0.093	0.097	0.093	0.099	0.104

Notes: This table presents the estimates of the average marginal effects computed based on a probit model. IIN = non-farm family business's income increased. All estimations include a constant, controls variables, state level fixed-effects, and are adjusted by cross-section weights. Standard errors are given in parenthesis and are clustered at the enumeration area level. *** p<0.01, ** p<0.05, * p<0.1

Table 34: Average effects of containment measures on the likelihood that the income from non-farm family business decreased

VARIABLES	(1) IDN	(2) IDN	(3) IDN	(4) IDN	(5) IDN	(6) IDN	(7) IDN
SAH	-0.0753	-0.0787*					
	(0.0504)	(0.0476)					
AGA	0.125**		0.0690				
	(0.0563)		(0.0532)				
ITR	0.0239			-0.0149			
	(0.0536)			(0.0510)			
CFL	0.0625				-0.00940		
	(0.0535)				(0.0497)		
NEBC	-0.0901					-0.0957*	
	(0.0614)					(0.0530)	
SCC	-0.134**						-0.125**
	(0.0595)						(0.0562)
Observations	671	671	671	671	671	671	671
Pseudo R2	0.110	0.091	0.090	0.088	0.087	0.093	0.096

Notes: This table presents the estimates of the average marginal effects computed based on a probit model. IDN = non-farm family business's income decreased. All estimations include a constant, controls variables, state level fixed-effects, and are adjusted by cross-section weights. Standard errors are given in parenthesis and are clustered at the enumeration area level. *** p<0.01, ** p<0.05, * p<0.1

Table 35: Average effects of containment measures on the likelihood that the income from wage employment increased

VARIABLES	(1) IIJ	(2) IIJ	(3) IIJ	(4) IIJ	(5) IIJ	(6) IIJ	(7) IIJ
SAH	0.0414	0.0520					
	(0.0834)	(0.0871)					
AGA	-0.219***		-0.180**				
	(0.0728)		(0.0723)				
ITR	0.0675			0.0320			
	(0.0725)			(0.0795)			
CFL	0.000785				0.00386		
	(0.0986)				(0.0905)		
NEBC	0.0341					0.00880	
	(0.0991)					(0.0926)	
SCC	0.0360						-0.00510
	(0.102)						(0.0954)
Observations	220	220	220	220	220	220	220
Pseudo R2	0.240	0.214	0.232	0.213	0.213	0.213	0.213

Notes: This table presents the estimates of the average marginal effects computed based on a probit model. IIJ = wage employment's income increased. All estimations include a constant, controls variables, state level fixed-effects, and are adjusted by cross-section weights. Standard errors are given in parenthesis and are clustered at the enumeration area level. *** p<0.01, ** p<0.05, * p<0.1

Table 36: Average effects of containment measures on the likelihood that the income from wage employment decreased

VARIABLES	(1) IDJ	(2) IDJ	(3) IDJ	(4) IDJ	(5) IDJ	(6) IDJ	(7) IDJ
SAH	-0.0357	-0.0206					
	(0.0987)	(0.0971)					
AGA	0.241***		0.214***				
	(0.0755)		(0.0790)				
ITR	-0.103			-0.0356			
	(0.0640)			(0.0701)			
CFL	-0.0294				-0.0121		
	(0.0902)				(0.0845)		
NEBC	0.0643					0.0691	
	(0.106)					(0.0934)	
SCC	-0.0329						0.0309
	(0.100)						(0.0906)
Observations	254	254	254	254	254	254	254
Pseudo R2	0.190	0.162	0.183	0.163	0.162	0.164	0.162

Notes: This table presents the estimates of the average marginal effects computed based on a probit model. IIJ = wage employment's income decreased. All estimations include a constant, controls variables, state level fixed-effects, and are adjusted by cross-section weights. Standard errors are given in parenthesis and are clustered at the enumeration area level. *** p<0.01, ** p<0.05, * p<0.1

Table 37: Test for sample selection bias using IIF as dependent variable

VARIABLES	Regression equation IIF	Selection equation IIF	Lambda estimation IIF
SAH	0.0844*	0.298*	
	(0.0473)	(0.171)	
AGA	-0.00622	0.0445	
	(0.0403)	(0.174)	
ITR	-0.0422	0.109	
	(0.0413)	(0.202)	
CFL	-0.0606	0.270	
	(0.0423)	(0.191)	
NEBC	-0.00770	-0.452*	
	(0.0573)	(0.231)	
SCC	-0.0300	0.220	
	(0.0500)	(0.239)	
HiredShare	0.0318	0.208	
	(0.0633)	(0.291)	
ProcessedShare	0.269**	-0.00876	
	(0.113)	(0.463)	
Land	-0.00399	-0.00891	
	(0.0125)	(0.0669)	
LivestockValue	-2.00e-08	5.45e-07	
	(4.68e-08)	(5.01e-07)	
AssetsValue	-2.89e-09	5.15e-09	
	(3.20e-09)	(3.83e-08)	
SafetyNet	-0.0802	0.384	
	(0.0555)	(0.314)	
HHindex	0.0268	0.0816	
	(0.0688)	(0.318)	
education		-0.0106	
		(0.0172)	
radio		0.360**	
		(0.156)	
lambda			-0.251
			(0.437)
Constant	0.335***	1.112***	
	(0.110)	(0.361)	
Observations	872	872	872

Note: The variables' definitions are provided in table 26. Standard errors are given in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table 38: Test for sample selection bias using IDF as dependent variable

VARIABLES	Regression equation IDF	Selection equation IDF	Lambda estimation IDF
SAH	-0.0937*	0.298*	
	(0.0496)	(0.171)	
AGA	0.0459	0.0445	
	(0.0422)	(0.174)	
ITR	0.00636	0.109	
	(0.0432)	(0.202)	
CFL	0.0185	0.270	
	(0.0443)	(0.191)	
NEBC	-0.000661	-0.452*	
	(0.0600)	(0.231)	
SCC	0.0248	0.220	
	(0.0524)	(0.239)	
HiredShare	-0.103	0.208	
	(0.0663)	(0.291)	
ProcessedShare	-0.238**	-0.00876	
	(0.119)	(0.463)	
Land	0.0158	-0.00891	
	(0.0131)	(0.0669)	
LivestockValue	-3.73e-08	5.45e-07	
	(4.90e-08)	(5.01e-07)	
AssetsValue	2.57e-09	5.15e-09	
	(3.34e-09)	(3.83e-08)	
SafetyNet	0.105*	0.384	
	(0.0581)	(0.314)	
HHindex	-0.0357	0.0816	
	(0.0720)	(0.318)	
education		-0.0106	
		(0.0172)	
radio		0.360**	
		(0.156)	
lambda			0.183
			(0.459)
Constant	0.584***	1.112***	
	(0.116)	(0.361)	
Observations	872	872	872

Note: The variables' definitions are provided in table 26. Standard errors are given in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX A2: APPENDICES FOR ESSAY 2

Table 39: Impact of conflicts on technical efficiency estimated using pooled Tobit

	(1) *TECRS*	(2) *TEVRS*	(3) *SE*
Fatalities per 100 persons	-0.240*	-0.257*	-0.0576
	(0.141)	(0.142)	(0.0965)
Share of trade in GDP	-0.000947**	-0.00198***	0.000195
	(0.000433)	(0.000456)	(0.000304)
Share of FDI in GDP	-0.00107	-0.00125	0.000442
	(0.00146)	(0.00148)	(0.00103)
Constant	1.078***	1.232***	1.031***
	(0.0279)	(0.0322)	(0.0192)
Observations	861	860	857

Notes: Estimation by pooled Tobit with upper limit equal to 1. Standard errors are reported in parentheses. Dependent variables are: TECRS (Technical Efficiency computed assuming Constant Return to Scale), TEVRS (Technical Efficiency computed assuming Variable Return to Scale), SE (Scale Efficiency). *** p<0.01, ** p<0.05, * p<0.1

Table 40: Impact of conflicts on technical efficiency estimated using CRE Tobit

	(1) *TECRS*	(2) *TEVRS*	(3) *SE*
Fatalities per 100 persons	0.0352	-0.971	-0.00980
	(0.139)	(9.342)	(0.0814)
Average of Fatalities per 100 persons	-3.970***	-412.6***	-1.427
	(0.523)	(35.34)	(1.387)
Share of trade in GDP	-0.000912**	0.360***	-0.000155
	(0.000405)	(0.0355)	(0.000601)
Share of FDI in GDP	-0.00138	-0.322***	0.00152
	(0.00138)	(0.104)	(0.00104)
Constant	1.085***	13.54**	1.115***
	(0.0633)	(5.533)	(0.0622)
Observations	861	860	857
Number of id	39	39	39

Notes: Estimation by CRE Tobit with upper limit equal to 1. Standard errors are reported in parentheses. Dependent variables are: TECRS (Technical Efficiency computed assuming Constant Return to Scale), TEVRS (Technical Efficiency computed assuming Variable Return to Scale), SE (Scale Efficiency). *** p<0.01, ** p<0.05, * p<0.1

Table 41: Impact of droughts deaths on technical efficiency estimated using pooled Tobit

	(1) TECRS	(2) TEVRS	(3) SE
Droughts deaths per 100,000 persons	-0.0275	-0.0657	0.0116
	(0.0737)	(0.0749)	(0.0506)
Share of trade in GDP	-0.000967**	-0.00202***	0.000194
	(0.000435)	(0.000459)	(0.000304)
Share of FDI in GDP	-0.00116	-0.00136	0.000422
	(0.00146)	(0.00149)	(0.00103)
Constant	1.079***	1.235***	1.031***
	(0.0281)	(0.0325)	(0.0193)
Observations	861	860	857

Notes: Estimation by pooled Tobit with upper limit equal to 1. Standard errors are reported in parentheses. Dependent variables are: TECRS (Technical Efficiency computed assuming Constant Return to Scale), TEVRS (Technical Efficiency computed assuming Variable Return to Scale), SE (Scale Efficiency). *** p<0.01, ** p<0.05, * p<0.1

Table 42: Impact of droughts deaths on technical efficiency estimated using CRE Tobit

	(1) *TECRS*	(2) *TEVRS*	(3) *SE*
Droughts deaths per 100,000 persons	-0.0321	-0.0377	0.0106
	(0.0757)	(5.542)	(0.0419)
Average of Droughts deaths per 100,000 persons	0.500	956.2***	-0.337
	(0.398)	(30.66)	(1.152)
Share of trade in GDP	-0.000936**	0.783***	-0.000173
	(0.000432)	(0.0417)	(0.000601)
Share of FDI in GDP	-0.00102	-0.232*	0.00151
	(0.00146)	(0.120)	(0.00103)
Constant	1.058***	194.7***	1.110***
	(0.0673)	(6.570)	(0.0630)
Observations	861	860	857
Number of id	39	39	39

Notes: Estimation by CRE Tobit with upper limit equal to 1. Standard errors are reported in parentheses. Dependent variables are: TECRS (Technical Efficiency computed assuming Constant Return to Scale), TEVRS (Technical Efficiency computed assuming Variable Return to Scale), SE (Scale Efficiency). *** p<0.01, ** p<0.05, * p<0.1

Table 43: Impact of droughts events on technical efficiency estimated using pooled Tobit

	(1) *TECRS*	(2) *TEVRS*	(3) *SE*
Droughts events per 100,000 persons	-1.574	-1.198	-0.275
	(1.271)	(1.347)	(0.903)
Share of trade in GDP	-0.000860*	-0.00192***	0.000209
	(0.000442)	(0.000466)	(0.000309)
Share of FDI in GDP	-0.00126	-0.00143	0.000404
	(0.00146)	(0.00149)	(0.00103)
Constant	1.077***	1.232***	1.031***
	(0.0280)	(0.0324)	(0.0193)
Observations	861	860	857

Notes: Estimation by pooled Tobit with upper limit equal to 1. Standard errors are reported in parentheses. Dependent variables are: TECRS (Technical Efficiency computed assuming Constant Return to Scale), TEVRS (Technical Efficiency computed assuming Variable Return to Scale), SE (Scale Efficiency). *** p<0.01, ** p<0.05, * p<0.1

Table 44: Impact of droughts events on technical efficiency estimated using CRE Tobit

	(1) *TECRS*	(2) *TEVRS*	(3) *SE*
Droughts events per 100,000 persons	-1.115	-101.4	0.200
	(0.810)	(117.7)	(0.934)
Average of *Droughts events per 100,000 persons*	9.522***	15,519***	0.245
	(2.638)	(363.8)	(10.68)
Share of trade in GDP	0.00166***	0.504***	-0.000185
	(0.000298)	(0.0388)	(0.000614)
Share of FDI in GDP	0.000933	-0.0930	0.00152
	(0.000804)	(0.0980)	(0.00104)
Constant	0.866***	55.25***	1.107***
	(0.0366)	(5.230)	(0.0643)
Observations	861	860	857
Number of id	39	39	39

Notes: Estimation by CRE Tobit with upper limit equal to 1. Standard errors are reported in parentheses. Dependent variables are: TECRS (Technical Efficiency computed assuming Constant Return to Scale), TEVRS (Technical Efficiency computed assuming Variable Return to Scale), SE (Scale Efficiency). *** p<0.01, ** p<0.05, * p<0.1

APPENDIX A3: APPENDICES FOR ESSAY 3

Table 45: Periods of data collection and conflict short-term measurement

Survey wave	Survey wave period	Survey cycle	Survey data collection start date	Survey data collection end date	Conflict measurement start date (1 year period)	Conflict measurement end date (1 year period)
1	2010-2011	Post-planting	08-2010	10-2010	2009-08-01	2010-07-31
1	2010-2011	Post-Harvest	02-2011	04-2011	2010-02-01	2011-01-31
2	2012-2013	Post-planting	09-2012	11-2012	2011-09-01	2012-08-31
2	2012-2013	Post-Harvest	02-2013	04-2013	2012-02-01	2013-01-31
3	2015-2016	Post-planting	09-2015	11-2015	2014-09-01	2015-08-31
3	2015-2016	Post-Harvest	02-2016	04-2016	2015-02-01	2016-01-31
4	2018-2019	Post-planting	07-2018	09-2018	2017-07-01	2018-06-30
4	2018-2019	Post-Harvest	01-2019	02-2019	2018-01-01	2018-12-31

Source: World Bank and authors calculations

Table 46: Periods of data collection and conflict long-term measurement

Survey wave	Survey wave period	Survey cycle	Survey data collection start date	Survey data collection end date	Conflict measurement start date (from the first ACLED data)	Conflict measurement end date (from the first ACLED data)
1	2010-2011	Post-planting	08-2010	10-2010	01-01-1997	31-07-2010
1	2010-2011	Post-Harvest	02-2011	04-2011	01-01-1997	31-01-2011
2	2012-2013	Post-planting	09-2012	11-2012	01-01-1997	31-08-2012
2	2012-2013	Post-Harvest	02-2013	04-2013	01-01-1997	31-01-2013
3	2015-2016	Post-planting	09-2015	11-2015	01-01-1997	31-08-2015
3	2015-2016	Post-Harvest	02-2016	04-2016	01-01-1997	31-01-2016
4	2018-2019	Post-planting	07-2018	09-2018	01-01-1997	30-06-2018
4	2018-2019	Post-Harvest	01-2019	02-2019	01-01-1997	31-12-2018

Source: World Bank and authors calculations

Table 47: Sensitivity analysis of the effects of conflicts on types of work differentiated by gender

	Family farm enterprises		Family non-farm enterprises		Employment		Diversification	
	Dependent variables							
	M	F	M	F	M	F	M	F
Panel A: Short-term conflict measurement method								
5 km around the individual's household	-0.000300***	-0.000298***	2.38e-05	7.61e-05	9.82e-05	0.000203**	-0.000177	-1.89e-05
	(8.74e-05)	(9.10e-05)	(0.000111)	(0.000100)	(9.40e-05)	(8.14e-05)	(0.000172)	(0.000164)
20 km around the individual's household	-6.29e-05	-7.00e-05	4.39e-05	5.21e-05	-9.54e-06	1.64e-05	-2.85e-05	-1.46e-06
	(5.29e-05)	(6.36e-05)	(5.03e-05)	(5.41e-05)	(4.37e-05)	(4.32e-05)	(8.43e-05)	(9.60e-05)
40 km around the individual's household	-6.36e-05*	-0.000102**	3.88e-05	1.25e-05	5.09e-06	2.12e-05	-1.96e-05	-6.83e-05
	(3.85e-05)	(4.68e-05)	(3.36e-05)	(3.45e-05)	(2.68e-05)	(2.72e-05)	(5.76e-05)	(6.81e-05)
LGA-based	-0.000135*	-0.000270***	-1.74e-05	-1.25e-05	-5.98e-05	-7.11e-06	-0.000212*	-0.000289**
	(7.54e-05)	(9.78e-05)	(7.05e-05)	(6.85e-05)	(5.10e-05)	(4.17e-05)	(0.000109)	(0.000133)
Long-term conflict measurement method								
5 km around the individual's household	-0.000190***	-0.000125***	7.66e-05*	6.30e-05*	8.82e-05**	8.86e-05***	-2.47e-05	2.64e-05
	(3.78e-05)	(2.46e-05)	(3.99e-05)	(3.44e-05)	(4.00e-05)	(2.84e-05)	(6.11e-05)	(5.27e-05)
20 km around the individual's household	-0.000112***	-8.56e-05***	6.72e-05***	3.60e-05*	2.48e-05	3.58e-05**	-2.00e-05	-1.38e-05
	(2.49e-05)	(2.35e-05)	(2.18e-05)	(2.15e-05)	(2.01e-05)	(1.57e-05)	(3.87e-05)	(3.92e-05)
40 km around the individual's household	-5.84e-05***	-7.10e-05***	4.40e-05***	1.52e-05	1.39e-05	3.39e-05***	-4.35e-07	-2.19e-05
	(1.82e-05)	(1.94e-05)	(1.59e-05)	(1.61e-05)	(1.42e-05)	(1.18e-05)	(2.83e-05)	(2.97e-05)
LGA-based	-9.99e-05***	-0.000127***	2.83e-05	-1.45e-05	1.86e-05	7.50e-06	-5.29e-05	-0.000134***
	(3.26e-05)	(2.99e-05)	(2.97e-05)	(2.49e-05)	(2.45e-05)	(1.65e-05)	(5.22e-05)	(4.88e-05)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 48: Sensitivity analysis of the effects of conflicts on employment in agriculture differentiated by gender

	WorksInAgri		AgriHoursPP		AgriHoursPH	
	M	F	M	F	M	F
Panel A: Short-term conflict measurement method						
5 km around the individual's household	-0.000167*	-0.000193	0.00783	-0.0119	0.0111	-0.00333
	(9.33e-05)	(0.000246)	(0.00554)	(0.0123)	(0.00736)	(0.0138)
20 km around the individual's household	-9.99e-05	-0.000173	-0.00493	-0.0158**	-0.00820	-0.0160
	(6.32e-05)	(0.000114)	(0.00474)	(0.00685)	(0.00562)	(0.0100)
40 km around the individual's household	-1.08e-06	-5.83e-05	-0.00371	-0.0104*	0.000918	-0.0119
	(6.32e-05)	(9.51e-05)	(0.00421)	(0.00613)	(0.0125)	(0.00905)
LGA-based	-0.000178**	-8.94e-05	-0.0147*	-0.0303**	-0.0187*	-0.0136
	(8.29e-05)	(0.000210)	(0.00788)	(0.0141)	(0.0113)	(0.0203)
Panel B: Long-term conflict measurement method						
5 km around the individual's household	-0.000119*	0.000167	0.00782**	0.0107	0.000373	0.0120**
	(6.54e-05)	(0.000143)	(0.00380)	(0.00693)	(0.00431)	(0.00583)
20 km around the individual's household	-0.000364***	-0.000116	-0.000577	0.00405	-0.00832	0.000817
	(0.000120)	(0.000122)	(0.00648)	(0.00737)	(0.00680)	(0.00494)
40 km around the individual's household	2.23e-05	-3.96e-05	0.00255	0.00933	0.000280	-0.00360
	(8.10e-05)	(0.000101)	(0.00465)	(0.00598)	(0.00401)	(0.00490)
LGA-based	-0.000317	-0.000302	-0.00386	-0.0138	-0.00593	-0.000349
	(0.000217)	(0.000357)	(0.00813)	(0.0113)	(0.00735)	(0.00633)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 49: Sensitivity analysis of the effects of conflicts on employment in manufacturing differentiated by gender

	WorksInManufacture		ManufactureHoursPP		ManufactureHoursPH	
	M	F	M	F	M	F
Panel A: Short-term conflict measurement method						
5 km around the individual's household	-0.000215	0.000449	-0.00613	0.0133	0.000815	0.0175*
	(0.000295)	(0.000333)	(0.0111)	(0.00995)	(0.0107)	(0.00947)
20 km around the individual's household	5.66e-05	0.000108	-0.00172	0.00139	0.00465	0.00398
	(9.59e-05)	(0.000120)	(0.00270)	(0.00311)	(0.00590)	(0.00483)
40 km around the individual's household	7.23e-06	0.000102	-0.000290	0.000541	0.00567	0.00932**
	(6.50e-05)	(1.00e-04)	(0.00177)	(0.00294)	(0.00387)	(0.00414)
LGA-based	6.08e-05	1.31e-05	0.000374	0.00116	0.00359	0.00949
	(5.75e-05)	(0.000172)	(0.00245)	(0.00532)	(0.00436)	(0.00722)
Panel B: Long-term conflict measurement method						
5 km around the individual's household	-0.000176	0.000155	0.000956	0.00472	0.000590	0.0131*
	(0.000193)	(0.000197)	(0.00626)	(0.00551)	(0.00554)	(0.00714)
20 km around the individual's household	8.79e-05	-4.76e-05	0.000113	-0.000697	0.00526	0.00638
	(0.000127)	(0.000177)	(0.00344)	(0.00489)	(0.00363)	(0.00529)
40 km around the individual's household	0.000144*	6.89e-05	0.00468***	0.00400	0.00428**	0.00450
	(7.56e-05)	(9.58e-05)	(0.00173)	(0.00322)	(0.00203)	(0.00385)
LGA-based	0.000255	0.000141	0.00748	0.0120	0.00660	0.0254***
	(0.000173)	(0.000177)	(0.00530)	(0.00949)	(0.00461)	(0.00556)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 50: Sensitivity analysis of the effects of conflicts on employment in services differentiated by gender

	WorksInServices		ServicesHoursPP		ServicesHoursPH	
	M	F	M	F	M	F
Panel A: Short-term conflict measurement method						
5 km around the individual's household	7.79e-06	0.000313	-0.0495***	-0.0363	-0.0165	-0.00300
	(0.000151)	(0.000208)	(0.0187)	(0.0356)	(0.0215)	(0.0168)
20 km around the individual's household	-1.76e-05	0.000479***	-0.0100	0.000155	-0.00292	0.0119
	(0.000123)	(0.000134)	(0.00618)	(0.0108)	(0.00988)	(0.0114)
40 km around the individual's household	-8.76e-06	0.000369***	-0.00675	-0.000157	-0.0110	0.00195
	(9.40e-05)	(0.000107)	(0.00504)	(0.00701)	(0.00817)	(0.00920)
LGA-based	7.26e-05	0.000643***	-0.00607	-0.00121	-0.00756	0.0126
	(0.000153)	(0.000210)	(0.00807)	(0.00503)	(0.0112)	(0.0140)
Panel B: Long-term conflict measurement method						
5 km around the individual's household	3.09e-05	-0.000173	-0.0202	-0.0277	-0.0192	-0.00271
	(0.000101)	(0.000178)	(0.0123)	(0.0214)	(0.0121)	(0.0100)
20 km around the individual's household	-5.83e-05	-0.000132	-0.00926	-0.00200	-0.00809	0.00881
	(0.000122)	(0.000175)	(0.00937)	(0.0135)	(0.00728)	(0.0102)
40 km around the individual's household	-0.000161*	-0.000287**	-0.0151***	-0.00507	-0.0117	0.00262
	(9.23e-05)	(0.000122)	(0.00515)	(0.00639)	(0.00722)	(0.00664)
LGA-based	1.99e-05	-0.000155	-0.0180	-0.0146	-0.0159	0.0117
	(0.000152)	(0.000200)	(0.0131)	(0.0144)	(0.0147)	(0.0142)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 51: Sensitivity analysis of the effects of conflicts on types of work differentiated by skill levels

	Dependent variables							
	Family farm enterprises		Family non-farm enterprises		Employment		Diversification	
	LS	HS	LS	HS	LS	HS	LS	HS
Panel A: Short-term conflict measurement method								
5 km around the individual's household	-0.000333***	0.000188	0.000112	-0.000148	0.000118*	0.000147	-0.000104	0.000188
	(7.12e-05)	(0.000202)	(8.57e-05)	(0.000212)	(6.78e-05)	(0.000266)	(0.000133)	(0.000382)
20 km around the individual's household	-7.77e-05*	0.000235*	5.96e-05	-0.000233	-1.67e-05	0.000167	-3.48e-05	0.000171
	(4.37e-05)	(0.000138)	(3.83e-05)	(0.000159)	(3.07e-05)	(0.000189)	(6.59e-05)	(0.000264)
40 km around the individual's household	-9.23e-05***	0.000209**	3.07e-05	-0.000130	5.66e-06	0.000106	-5.59e-05	0.000185
	(3.20e-05)	(0.000106)	(2.52e-05)	(0.000110)	(1.88e-05)	(0.000131)	(4.60e-05)	(0.000176)
LGA-based	-0.000198***	-0.000445	-9.19e-06	-0.000638*	-1.28e-05	0.000349	-0.000220***	-0.000731
	(6.38e-05)	(0.000330)	(4.91e-05)	(0.000334)	(3.41e-05)	(0.000315)	(8.49e-05)	(0.000575)
Long-term conflict measurement method								
5 km around the individual's household	-0.000202***	0.000101	8.59e-05***	7.09e-05	8.08e-05***	5.45e-05	-3.49e-05	0.000226**
	(2.31e-05)	(6.69e-05)	(3.05e-05)	(7.10e-05)	(2.70e-05)	(0.000107)	(4.31e-05)	(0.000111)
20 km around the individual's household	-0.000116***	0.000109*	5.78e-05***	3.31e-05	2.60e-05**	5.50e-05	-3.22e-05	0.000197*
	(1.87e-05)	(6.21e-05)	(1.62e-05)	(6.46e-05)	(1.28e-05)	(9.57e-05)	(2.90e-05)	(0.000102)
40 km around the individual's household	-7.22e-05***	0.000110**	3.66e-05***	1.03e-05	2.14e-05**	3.85e-05	-1.43e-05	0.000159**
	(1.44e-05)	(4.93e-05)	(1.19e-05)	(5.06e-05)	(9.22e-06)	(7.74e-05)	(2.17e-05)	(7.92e-05)
LGA-based	-0.000118***	-9.36e-05	1.96e-05	-0.000174	2.84e-05*	0.000136	-6.97e-05*	-0.000132
	(2.41e-05)	(0.000100)	(2.02e-05)	(0.000163)	(1.53e-05)	(0.000129)	(3.77e-05)	(0.000243)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 52: Sensitivity analysis of the effects of conflicts on employment in agriculture differentiated by skill levels

	WorksInAgri		AgriHoursPP		AgriHoursPH	
	LS	HS	LS	HS	LS	HS
Panel A: Short-term conflict measurement method						
5 km around the individual's household	-0.000350**	2.85e-05	-0.00440	0.0228	0.00307	0.00404
	(0.000159)	(0.000226)	(0.00770)	(0.0147)	(0.0110)	(0.0123)
20 km around the individual's household	-0.000173***	-5.48e-05	-0.0108**	-0.00422	-0.0166***	-1.37e-05
	(6.40e-05)	(0.000179)	(0.00458)	(0.00954)	(0.00644)	(0.0108)
40 km around the individual's household	-6.44e-05	6.88e-06	-0.00695*	-0.0124	-0.00419	-0.0163
	(5.57e-05)	(0.000180)	(0.00410)	(0.00751)	(0.0104)	(0.0147)
LGA-based	-0.000151	0.000106	-0.0217***	0.00829	-0.0206*	0.0338
	(9.62e-05)	(0.000339)	(0.00783)	(0.0192)	(0.0111)	(0.0383)
Panel B: Long-term conflict measurement method						
5 km around the individual's household	-8.00e-05	0.000120	0.00871*	0.0198**	0.00191	0.00187
	(9.08e-05)	(0.000144)	(0.00482)	(0.00999)	(0.00571)	(0.00699)
20 km around the individual's household	-0.000348***	0.000116	-0.00224	0.0241**	-0.0102	0.00780
	(0.000111)	(0.000166)	(0.00629)	(0.0101)	(0.00635)	(0.00889)
40 km around the individual's household	1.02e-06	0.000205	0.00475	0.0169	-0.00352	0.00734
	(7.56e-05)	(0.000192)	(0.00423)	(0.0105)	(0.00354)	(0.0100)
LGA-based	-0.000324	0.000133	-0.00991	0.0257*	-0.00970	0.0141
	(0.000247)	(0.000271)	(0.00760)	(0.0142)	(0.00625)	(0.0216)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 53: Sensitivity analysis of the effects of conflicts on employment in manufacturing differentiated by skill levels

	WorksInManufacture		ManufactureHoursPP		ManufactureHoursPH	
	LS	HS	LS	HS	LS	HS
Panel A: Short-term conflict measurement method						
5 km around the individual's household	-0.000160	-0.000184	-0.00238	-0.0141	-0.000657	0.00253
	(0.000438)	(0.000389)	(0.0170)	(0.0103)	(0.0128)	(0.00543)
20 km around the individual's household	1.46e-05	4.62e-05	-0.00126	-0.00469	0.00141	-0.000691
	(7.75e-05)	(0.000210)	(0.00239)	(0.00355)	(0.00449)	(0.00282)
40 km around the individual's household	-1.15e-06	7.02e-05	-0.000620	-0.00140	0.00616*	0.00288
	(5.60e-05)	(0.000190)	(0.00176)	(0.00219)	(0.00339)	(0.00251)
LGA-based	2.74e-05	-0.000414	0.000447	-0.0277	0.00322	0.00102
	(7.23e-05)	(0.000684)	(0.00259)	(0.0173)	(0.00378)	(0.0139)
Panel B: Long-term conflict measurement method						
5 km around the individual's household	5.62e-06	-0.000263	0.00690	-0.0104	0.00380	0.000940
	(0.000264)	(0.000224)	(0.00781)	(0.00785)	(0.00789)	(0.00419)
20 km around the individual's household	7.15e-05	-0.000303	0.000464	-0.0104	0.00553	-0.00147
	(0.000127)	(0.000228)	(0.00323)	(0.00730)	(0.00385)	(0.00352)
40 km around the individual's household	0.000124*	-0.000114	0.00425**	-0.00378	0.00475**	0.00268
	(6.74e-05)	(0.000186)	(0.00176)	(0.00534)	(0.00228)	(0.00309)
LGA-based	0.000244	-0.000617	0.00764	-0.0248	0.0118**	0.000330
	(0.000152)	(0.000483)	(0.00524)	(0.0152)	(0.00461)	(0.0130)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 54: Sensitivity analysis of the effects of conflicts on employment in services differentiated by skill levels

	WorksInServices		ServicesHoursPP		ServicesHoursPH	
	LS	HS	LS	HS	LS	HS
Panel A: Short-term conflict measurement method						
5 km around the individual's household	0.000248	0.000301*	-0.0132	-0.0256	0.0154	0.0117
	(0.000211)	(0.000165)	(0.0248)	(0.0311)	(0.0246)	(0.0185)
20 km around the individual's household	0.000224**	7.21e-05	-0.000524	-0.0154	0.0112	0.00370
	(0.000101)	(6.86e-05)	(0.00614)	(0.0170)	(0.00926)	(0.0120)
40 km around the individual's household	0.000177**	1.51e-05	-0.00104	-0.00319	-0.00318	0.0157
	(8.24e-05)	(4.18e-05)	(0.00441)	(0.0147)	(0.00727)	(0.0129)
LGA-based	0.000255*	0.000223	0.00155	-0.00856	0.00790	-0.00594
	(0.000133)	(0.000188)	(0.00544)	(0.0417)	(0.00890)	(0.0427)
Panel B: Long-term conflict measurement method						
5 km around the individual's household	-0.000122	0.000246**	-0.0150	-0.00310	-0.00562	0.00899
	(0.000134)	(0.000119)	(0.0149)	(0.0220)	(0.0148)	(0.0119)
20 km around the individual's household	-8.78e-05	0.000292**	-0.00153	-0.00574	0.00452	0.00602
	(0.000122)	(0.000114)	(0.00912)	(0.0205)	(0.00708)	(0.0105)
40 km around the individual's household	-0.000229***	0.000156*	-0.00900**	-0.0118	-0.00580	-0.00156
	(8.13e-05)	(8.04e-05)	(0.00444)	(0.0170)	(0.00627)	(0.0111)
LGA-based	-0.000116	0.000319*	-0.0108	0.0176	-0.00131	-2.62e-05
	(0.000151)	(0.000174)	(0.0119)	(0.0321)	(0.0123)	(0.0329)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 55: Impact of the number of incidents on the types of work

	Dependent variables			
	Family farm enterprises	Family non-farm enterprises	Employment	Diversification
Panel A: Short-term conflict measurement method				
5 km around the individual's household	-0.00154***	-0.00115**	0.000174	-0.00252***
	(0.000329)	(0.000524)	(0.000495)	(0.000767)
20 km around the individual's household	-0.000705***	-0.000236	0.000166	-0.000775**
	(0.000225)	(0.000239)	(0.000216)	(0.000389)
40 km around the individual's household	-0.000918***	2.73e-05	0.000467***	-0.000424
	(0.000218)	(0.000217)	(0.000178)	(0.000353)
LGA-based	-0.00115***	-8.74e-05	0.000474	-0.000761
	(0.000353)	(0.000408)	(0.000364)	(0.000662)
Panel B: Long-term conflict measurement method				
5 km around the individual's household	-0.00116***	0.000247	0.000492***	-0.000422*
	(0.000102)	(0.000154)	(0.000125)	(0.000218)
20 km around the individual's household	-0.000463***	0.000161***	9.79e-05*	-0.000204**
	(6.30e-05)	(6.12e-05)	(5.63e-05)	(0.000101)
40 km around the individual's household	-0.000425***	0.000103*	0.000123**	-0.000199**
	(5.62e-05)	(5.76e-05)	(4.80e-05)	(8.69e-05)
LGA-based	-0.000802***	0.000170	0.000181*	-0.000450**
	(0.000108)	(0.000123)	(0.000100)	(0.000192)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 56: Impact of the number of incidents on employment in agriculture

	WorksInAgri	AgriHoursPP	AgriHoursPH
Panel A: Short-term conflict measurement method			
5 km around the individual's household	-0.000923**	-0.000437	0.0139
	(0.000439)	(0.0224)	(0.0252)
20 km around the individual's household	-0.00190***	-0.0531*	-0.0276
	(0.000586)	(0.0294)	(0.0265)
40 km around the individual's household	-0.000855	-0.0267	-0.0294
	(0.000584)	(0.0289)	(0.0302)
LGA-based	-0.00372***	-0.114**	-0.0378
	(0.00128)	(0.0498)	(0.0317)
Panel B: Long-term conflict measurement method			
5 km around the individual's household	-0.000172	0.0209*	0.00978
	(0.000211)	(0.0107)	(0.0116)
20 km around the individual's household	-0.000984***	-0.000193	0.00491
	(0.000379)	(0.0165)	(0.0144)
40 km around the individual's household	-0.000458	0.0296*	0.0146
	(0.000332)	(0.0172)	(0.0133)
LGA-based	-0.00215***	-0.0255	-0.00958
	(0.000715)	(0.0277)	(0.0193)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 57: Impact of the number of incidents on employment in manufacturing

	WorksInManufacture	ManufactureHoursPP	ManufactureHoursPH
Panel A: Short-term conflict measurement method			
5 km around the individual's household	-0.000767	0.0234	0.0175
	(0.00105)	(0.0319)	(0.0357)
20 km around the individual's household	0.000583	-0.00503	0.0316
	(0.000659)	(0.0158)	(0.0225)
40 km around the individual's household	0.00102*	0.0131	0.0547***
	(0.000557)	(0.0141)	(0.0194)
LGA-based	0.000538	0.0294	0.0639*
	(0.000903)	(0.0423)	(0.0385)
Panel B: Long-term conflict measurement method			
5 km around the individual's household	-0.000451	0.0124	8.73e-05
	(0.000477)	(0.0133)	(0.0136)
20 km around the individual's household	-5.16e-05	-0.00221	0.00900
	(0.000358)	(0.0103)	(0.0111)
40 km around the individual's household	0.000139	0.00946	0.0162*
	(0.000296)	(0.00837)	(0.00894)
LGA-based	-2.42e-05	0.0143	0.0217
	(0.000443)	(0.0221)	(0.0174)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 58: Impact of the number of incidents on employment in services

	WorksInServices	ServicesHoursPP	ServicesHoursPH
Panel A: Short-term conflict measurement method			
5 km around the individual's household	0.000760	-0.227***	-0.0942
	(0.000486)	(0.0737)	(0.0755)
20 km around the individual's household	0.000359	-0.0820	-0.0260
	(0.000637)	(0.0506)	(0.0443)
40 km around the individual's household	0.000236	-0.0919**	-0.0739*
	(0.000616)	(0.0437)	(0.0410)
LGA-based	0.00114*	-0.106	-0.0712
	(0.000675)	(0.0958)	(0.0792)
Panel B: Long-term conflict measurement method			
5 km around the individual's household	6.73e-05	-0.0762**	-0.0493
	(0.000296)	(0.0348)	(0.0316)
20 km around the individual's household	-0.000184	-0.0225	-0.00934
	(0.000332)	(0.0305)	(0.0225)
40 km around the individual's household	-0.000783**	-0.0285	-0.0266
	(0.000339)	(0.0242)	(0.0196)
LGA-based	-8.63e-05	-0.00593	-0.0640
	(0.000432)	(0.0503)	(0.0405)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

Table 59: Attrition significance tests

	Dependent variables: individual observed in wave W		
	W = 2	W = 3	W = 4
Short-term fatalities within 5 km	0.00414**	0.00367***	-3.93e-05
	(0.00184)	(0.000860)	(0.000208)
Female	-0.111***	-0.148***	-0.0366
	(0.0299)	(0.0270)	(0.0246)
Age	0.0133***	0.00816**	-0.000433
	(0.00435)	(0.00382)	(0.00309)
Age squared	-0.000106*	5.90e-06	2.70e-05
	(6.07e-05)	(5.38e-05)	(4.10e-05)
Years of education	-0.0373***	-0.0386***	-0.00218
	(0.00425)	(0.00370)	(0.00296)
Age of household head	0.000330	-0.0153**	0.0237***
	(0.00743)	(0.00684)	(0.00637)
Age of household head squared	-0.000125*	-1.21e-06	-0.000243***
	(6.65e-05)	(5.99e-05)	(5.81e-05)
Household's land size	0.00795	-0.00522***	-0.00461
	(0.00584)	(0.00181)	(0.00529)
Household's livestock value	1.06e-08	2.92e-08	-2.77e-08**
	(2.00e-08)	(3.06e-08)	(1.19e-08)
Number of children in the household	0.0378***	0.0354***	0.00598
	(0.0118)	(0.00944)	(0.00765)
Value of household's assets	-4.36e-06	0.000344***	-1.32e-05*
	(1.44e-05)	(5.92e-05)	(6.76e-06)
Household's distance to nearest market	-0.00169***	0.00243***	0.000791***
	(0.000352)	(0.000328)	(0.000295)
Annual Precipitation	-0.000182***	8.44e-05***	-3.05e-05
	(2.28e-05)	(2.29e-05)	(2.08e-05)
Constant	2.178***	1.664***	-1.077***
	(0.210)	(0.199)	(0.178)
Observations	16,007	14,358	12,151
Pseudo R2	0.0509	0.0486	0.0034

Notes: This table reports the impacts of conflicts on the probability of attrition estimated using probit models. Each column represents a regression. Standard errors are given in parenthesis and are robust to heteroskedasticity and serial correlation. *** p<0.01, ** p<0.05, * p<0.1

Table 60: Effects of conflict on types of work estimated using inverse probability weighting

	Family farm enterprises	Family non-farm enterprises	Employment	Diversification
Panel A: Short-term conflict measurement method				
5 km around the individual's household	-0.000838***	0.000110	0.000288***	-0.000440***
	(7.49e-05)	(7.43e-05)	(6.58e-05)	(0.000112)
20 km around the individual's household	-0.000223***	2.58e-05	8.52e-05***	-0.000111***
	(3.16e-05)	(3.07e-05)	(2.60e-05)	(4.29e-05)
40 km around the individual's household	4.47e-05**	-1.15e-05	2.06e-05	5.38e-05*
	(2.24e-05)	(1.98e-05)	(1.65e-05)	(2.86e-05)
LGA-based	-0.000140***	-6.59e-05	9.10e-05***	-0.000115*
	(4.95e-05)	(4.41e-05)	(3.46e-05)	(6.08e-05)
Panel B: Long-term conflict measurement method				
5 km around the individual's household	-0.000241***	6.92e-05***	6.34e-05***	-0.000109***
	(1.05e-05)	(1.34e-05)	(1.14e-05)	(1.73e-05)
20 km around the individual's household	-0.000199***	7.57e-05***	2.48e-05***	-9.84e-05***
	(7.34e-06)	(8.21e-06)	(6.76e-06)	(1.06e-05)
40 km around the individual's household	-6.63e-05***	3.88e-05***	1.88e-06	-2.56e-05***
	(5.43e-06)	(4.89e-06)	(3.94e-06)	(6.93e-06)
LGA-based	-0.000112***	3.06e-05***	3.86e-05***	-4.29e-05***
	(9.91e-06)	(1.14e-05)	(9.58e-06)	(1.46e-05)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are robust to heteroskedasticity and serial correlation.

*** p<0.01, ** p<0.05, * p<0.1

Table 61: Effects of conflict on employment in agriculture estimated using inverse probability weighting

	WorksInAgri	AgriHoursPP	AgriHoursPH
Panel A: Short-term conflict measurement method			
5 km around the individual's household	-0.00250***	-0.0778***	-0.0369***
	(0.000201)	(0.00683)	(0.00817)
20 km around the individual's household	-0.000246***	-0.00987***	-0.00839**
	(6.16e-05)	(0.00232)	(0.00368)
40 km around the individual's household	4.38e-05	-0.000434	0.000515
	(4.37e-05)	(0.00174)	(0.00317)
LGA-based	-5.47e-05	-0.00723	-0.0102
	(0.000106)	(0.00456)	(0.00687)
Panel B: Long-term conflict measurement method			
5 km around the individual's household	-0.000377***	-0.0108***	-0.00868***
	(2.02e-05)	(0.000646)	(0.000611)
20 km around the individual's household	-0.000310***	-0.00870***	-0.00661***
	(1.35e-05)	(0.000479)	(0.000462)
40 km around the individual's household	-9.37e-05***	-0.00251***	-0.00167***
	(9.88e-06)	(0.000389)	(0.000393)
LGA-based	-0.000206***	-0.00602***	-0.00386***
	(1.59e-05)	(0.000633)	(0.000622)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are robust to heteroskedasticity and serial correlation.
*** p<0.01, ** p<0.05, * p<0.1

Table 62: Effects of conflict on employment in manufacturing estimated using inverse probability weighting

	WorksInManufacture	ManufactureHoursPP	ManufactureHoursPH
Panel A: Short-term conflict measurement method			
5 km around the individual's household	0.000466***	0.0115*	0.00669
	(0.000177)	(0.00681)	(0.00490)
20 km around the individual's household	9.45e-05**	-0.000130	0.00673***
	(3.99e-05)	(0.00111)	(0.00246)
40 km around the individual's household	6.18e-05**	-5.03e-05	0.00427**
	(2.72e-05)	(0.000932)	(0.00167)
LGA-based	5.89e-05	0.00118	0.00389
	(5.25e-05)	(0.00180)	(0.00363)
Panel B: Long-term conflict measurement method			
5 km around the individual's household	3.37e-05**	0.00115*	0.000950
	(1.53e-05)	(0.000644)	(0.000650)
20 km around the individual's household	5.15e-05***	0.00178***	0.00169***
	(9.78e-06)	(0.000394)	(0.000389)
40 km around the individual's household	2.70e-05***	0.000896***	0.000836***
	(5.57e-06)	(0.000225)	(0.000208)
LGA-based	4.43e-05***	0.00116**	0.000737
	(1.48e-05)	(0.000580)	(0.000584)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are robust to heteroskedasticity and serial correlation.
*** p<0.01, ** p<0.05, * p<0.1

Table 63: Effects of conflict on employment in services estimated using inverse probability weighting

	WorksInServices	ServicesHoursPP	ServicesHoursPH
Panel A: Short-term conflict measurement method			
5 km around the individual's household	0.00129***	0.0244***	0.0275***
	(0.000155)	(0.00916)	(0.00951)
20 km around the individual's household	0.000158***	-0.00602**	0.00449
	(5.26e-05)	(0.00283)	(0.00442)
40 km around the individual's household	2.57e-05	-0.00883***	-0.00375
	(3.81e-05)	(0.00192)	(0.00296)
LGA-based	4.39e-05	-0.0143***	-0.00304
	(8.81e-05)	(0.00367)	(0.00691)
Panel B: Long-term conflict measurement method			
5 km around the individual's household	0.000206***	0.00701***	0.00696***
	(1.62e-05)	(0.00120)	(0.00115)
20 km around the individual's household	0.000156***	0.00643***	0.00636***
	(1.14e-05)	(0.000755)	(0.000725)
40 km around the individual's household	5.68e-05***	0.00198***	0.00177***
	(8.46e-06)	(0.000445)	(0.000448)
LGA-based	0.000126***	0.00163	0.00292***
	(1.55e-05)	(0.00103)	(0.00103)

Notes: Each cell represents a regression and reports the coefficient associated with the impact of the conflict measure (in row) on the outcome of interest (in column). Individual, state, state-wave fixed effects and control variables are included in the regression but not reported in the table. Standard errors are given in parenthesis and are robust to heteroskedasticity and serial correlation.

*** p<0.01, ** p<0.05, * p<0.1