

THREE ESSAYS ON THE RELATIONSHIP BETWEEN VIOLENCE, URBANIZATION AND THE
AGRIFOOD-VALUE CHAIN

By

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ABSTRACT

The dynamics of violence and insecurity impose shocks on the general population that can cause devastation and limit market transactions. Violence shocks have led to drops in agricultural production, investment and labor decisions, amongst others. Moreover, the effects of armed confrontation, banditry and aggression have not been homogenous across the population and have differed based on socioeconomic levels linked to urbanization and geographical differences. Within agri-food research, literature has focused mostly on the effects of violence on farmers decisions and welfare without taking into account meso- level variables such as urbanization or other value chain actors, such as traders. The purpose of this work is to understand the relationship between violence and urbanization on the structuring of agri-food value chain as well as the actors within it.

The first essay analyzes how meso-level variables, access to value chains, violence levels and territorial characteristics of secondary/tertiary cities and their catchment areas (denominated rural-urban territories) have an effect firstly, on milk farmers market channel choice and secondly on the decision of milk farmers to adopt different technologies associated to breeding, pasture management and milking practices. For both analyses, we particularly focus on rural-urban development levels (degree of violence, urbanization, and urban proximity) and access to value chains, measured by the number of upstream and downstream traders, all while controlling for farmer micro characteristics.

The second paper studies the vulnerability of maize trader in Nigeria to exogenous shocks (such as climate, violence, or spoilage). We focus firstly on understanding the relationship among these shocks (that is, do they cluster or affect the trader as a “confluence”) and second on the

trader characteristics that make them more vulnerable. Specifically, we analyze if female, rural, and Northern (poorer region) traders more vulnerable to exogenous shocks than male, urban, and Southern traders. We find that There's a notable positive correlation between COVID and violence shocks, particularly affecting Northern regions, which bear a disproportionate burden of shocks due to poverty and rural violence. Gender also plays a role, with women more likely to experience violence shocks. Traders farming maize mitigate price shocks but become more vulnerable to violence shocks.

The final essay examines the impact of violent conflict on maize prices in Nigeria. Drawing on survey data from 1100 maize farmers in Nigeria in 2021, we analyze both violent events and the presence of non-state armed actors (NSAA), on maize prices in the locations where a trader's base is (i.e. his main stall/firm activity is located) as well as the location of their main supplier. We find that heightened violence correlates with increased maize prices, underlining the transaction cost aspect of violence and its hindrance to market mobility. Our analysis also highlights the significant interaction effect between violence and urban density, emphasizing the pronounced impact of violence on prices in urbanized areas.

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Dedicated to my parents Felipe and Lisa, and my sister Verónica

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LIST OF ABBREVIATIONS

AVC Agrifood value chains

RTD Rural territorial development

RUT Rural urban territory

NSAA non-state armed actors

LGA Local Government Area

CHAPTER 1
RURAL-URBAN DEVELOPMENT, VIOLENCE AND ACCESS TO VALUE CHAINS: AN ANALYSIS OF
MILK FARMER DECISIONS ON MARKET CHANNEL CHOICE AND TECHNOLOGY ADOPTION

I. ABSTRACT

This article analyzes how rural territories anchored by secondary/tertiary cities, denominated rural-urban territories (RUT), in the Southwest part of Colombia introduce spatial and territorial heterogeneity in the participation of farmers in restructured dairy value chains, and subsequent technology adoption. We look at how different sized RUTs (with an urban center between 15k-400k inhabitants) affect farmer participation in modern market channels, and in turn, how the probability of supplying to a specific market channel influences the use of concentrate, insemination, cooling tanks, fertilizer, and herbicide. All while controlling for farmer micro characteristics, as well as the level of rural territorial development (degree of violence, density of infrastructure, and urban proximity) and geographical differences.

Our findings reveal a joint effect of violence and urbanization levels on both the probability of selling to the modern market and the quantity of feed, insemination, and fertilizer/herbicide use, with varying impacts across technologies. While violence generally negatively affects technology adoption, its interaction with urbanization levels can mitigate risks. Moreover, we identify key determinants of market channel choice and technology adoption across different-sized rural-urban territories, emphasizing the inadequacy of one-size-fits-all agricultural policies. We find that farmers supplying modern channels exhibit a higher probability of technology adoption, yet adoption rates remain low overall. Despite larger farmers dominating modern market channels, small farmers are not excluded, underscoring the potential for smallholder participation with appropriate investments.

II. INTRODUCTION

In recent years there has been a rise of the modern milk market in low- and middle-income countries (LMICs) as well as the transformation of the agri-food value chains associated with it. This rise has happened in waves throughout LMICs, where Latin America and Eastern Europe have been the front runners (Dries et al., 2008), followed by Asia (Vandeplas, Minten and Swinnen, 2013), and more recently Africa (Van Campenhout, Minten and Swinnen, 2021). This phenomenon has been the result of a wave of liberalization policies that encouraged the inflow of foreign direct investment (FDI) (Reardon and Barrett, 2000), as well as the transformation of downstream segments, such as the rise of supermarkets and the consolidation of food processing (Farina 2002).

Sparked by this rise, two strands of literature have emerged: (1) one that has focused on the characteristics of farmers that participate within the modern milk market; and a (2) second that has studied the effect of modern dairy channel participation on farmers and farmer decisions and outcomes. Most studies treat these separately, but a few examine both, linking participation to outcomes like income and technology adoption (Vandeplas, Minten & Swinnen, 2013).

Strand (1) largely explores the relationship between modern market participation and farmer-level factors like incentives given by the modern market (prices, inputs, etc.), and most commonly, farmer size (Reardon et al, 2009). In fact, the debate on farm size has been particularly controversial; on one hand, some have argued that small farmers have been excluded from modern market participation given that they are more prone to risk, face higher costs and don't have the assets to make the necessary investments (Chen et al., 2011). On the other hand, some

argue that small-scale farmers are not excluded as they are able lower transaction costs, particularly when it comes to labor (Reardon et al, 2009).

Within the dairy literature, there have been contradicting results with regards to the participation of small farmers within modern milk markets. In Farina (2002) and Gutman (2002), the consolidation of the modern milk market in Brazil and Argentina led to the exclusion, and subsequent reduction in the participation of small farmers within the modern market. They found that many farmers were not able to make threshold investments that were imposed by these markets in order to achieve higher levels of quality and quantity. Nonetheless, in Dries and Swinnen, (2004), Dries et al. (2008) and White and Gordon (2006), the expansion of modern supply chains in Eastern Europe did not exclude small farmers. In this case, the modern market made investments in institutions and infrastructure that reduced transaction costs for small farmers, such as supporting collective collection centers or providing credit.

Another sub-strand within the market participation literature has focused on meso-level determinants; particularly with regards to different types of transaction costs that are generated by geographic or biophysical constraints (Barret et al. 2012). Most of the meso-level participation literature has focused on the transaction costs brought by distance to either the nearest village, processors or roads. The general consensus that increased distances to processors and paved roads elevate transportation expenses, spoilage risks, and challenges in locating buyers, all of which deter market engagement. For instance, Berdegúé, Hernández & Reardon (2008) and Hernández, Berdegúé & Reardon (2012) show a negative correlation between distance to processing plants and participation in modern channels, as well as a positive relationship between market inclusion and proximity to paved roads.

It is within the meso-level literature that we find the most gaps with regards to market channel participation, as few have delved into the rest of the transaction costs described by Barret et al. (2012). First of all, we find that few papers have looked into the relationship between market size and market participation. This sub-strand (market participation and market size) has focused on the effect of industrial organization on market access, and find that a higher quantity of buyers, input sellers, and other chain actors can reduce transaction costs, particularly information costs, that reduce the barriers to farmer participation in modern markets. . For instance, Hernández, Berdegúe, and Reardon (2012) found higher farmer inclusion in modern supply chains within more commercially developed districts. As well, Escobal & Caverio (2011) find a positive relationship between market access and districts with high concentration of medium- to large-scale processors. In the dairy sector, increased presence of collection centers has been linked to a higher likelihood of farmers selling to modern channels (Sharma, 2015). Still, these are only a handful of papers, which is surprising given the results we have seen so far.

A second gap relates to market channel participation and village size. This issue remains completely unexplored. The only exception is a paper by Vandeplas, Minten and Swinnen (2013) that studied both the size of the village center and the distance to the village as determinants of dairy modern market participation in India. They find that there is a significant positive relationship between village size and the probability of milk farmers selling to multinationals and cooperatives, suggesting that buyer's source more milk from larger villages with more milk surplus. This gap in the literature is surprising given the amount of literature on the relationship between transaction costs and agglomeration economies, particularly within the manufacturing sector (Picard and Zeng, 2005). This literature has found that costs are reduced in larger cities

because of firm selection (only the most productive firms survive) and agglomeration economies (interactions between firms are easier) (Combes et al. 2012).

We identified a third gap within the meso-level literature, as we have found no papers that looked into the effect of violence on market channel participation. In general, literature has focused the effects of violent shocks on economic expansion and on farmer decisions. On the expansion side, it has been shown that conflict and violence have direct and indirect effects on economic cost on production. Firstly, the destruction of private and public property and assets decreases the productive capacity of firms (Blattman and Miguel 2010; Ibáñez and Moya 2010b). Second, kidnappings and killings deteriorate human capital (De Walque 2006; Walque and Verwimp 2009). Third, this fall in productive capacity and human capital, leads to the contraction of the supply of goods and higher transaction costs (Justino 2011). This decrease in production leads to lower household income and consumption (Nanji et al. 2022).

Conflict can also lead to a change in behavior of households and firms' decisions, from profit maximizing to reduction in risk (Arias, Ibáñez, and Zambrano, 2017). When non-state actors take over a specific area, they can impose new governance structures, which leads to different overall institutions. Frequent changes of governance structures (from one group taking control over an area), can lead to uncertainty. Moreover, farmers in high-violence areas anticipate a greater likelihood of shocks (Adelaja and George, 2017), leading them to adjust behaviors to mitigate conflict-induced risks, often prioritizing risk minimization over profit. Exposure to violence also diminishes local trust and reduces willingness to engage in interpersonal exchanges, which are vital for market development (Cassar, Grosjean, and Whitt, 2013; Fafchamps, 2006). While the impact of violence on production decisions is evident, its effect on market participation

remains underexplored. We have found no papers that directly linked violence to farmers' market participation choices, leaving it unclear whether violence hinders integration into modern markets by limiting production or if modern channels might mitigate risk by offering better prices and input access.

The second strand of literature (2), modern market participation as a determinant of technology adoption, has been more widely studied. The relationship between value chain modernization and technology transfer in agriculture has been modeled by Kuijpers and Swinnen (2016), where they show that technology transfer through value chain can generate benefits to both the buyer and seller. Nonetheless, non-adoption is still very common and is normally linked to opportunity costs, contract enforcement and the amount of surplus generated by the technology. Empirical studies offer mixed findings: Schipmann and Qaim (2010) found that the entry of specialized companies in Thailand led to sweet pepper adoption, while Burkitbayeva, Janssen, and Swinnen (2019) observed no significant differences in hygiene practice adoption between milk farmers engaged in private channels and those who were not. These discrepancies may stem from farmers' capacities, where incentives from modern markets are insufficient or adoption methods are too complex.

As with modern market participation, the literature linking technology adoption and modern markets choice, has also had two separate sub-strands that have first focused on micro level characteristics and then on the meso-level ones. Within the micro-level characteristics, most literature has focused on scale as a determinant of technology adoption. There is also large debate on whether small farmers are excluded from technology adoption given the constraints on credit and assets (Reardon et al. 2009) or are they able to more easily implement these

technologies (Janssen and Swinnen 2019). For this reason, many papers have focused on what prevents small farmers from participating, and have focused on deterrents of threshold investments, such as institutional constraints and infrastructure, or on farmers' characteristics such as risk, uncertainty, and education (Uaiene 2008 and Feder et al. 1985).

Within the meso-level characteristics, as with modern market participation, we find that distance to the nearest road, processor or village has been deeply studied and consistently linked to technology adoption. Studies by Bernués and Herrero (2008) and Kebebe (2017) indicate that greater distances to markets not only hinder technology adoption but also affect farm configurations, such as herd size and specialization. Minten, Stifel, and Dorosh (2003) found that increased market distance correlates with reduced input use intensity, a conclusion echoed by Obare, Omamo, and Williams (1998) in Kenya. These findings suggest that longer distances elevate transportation costs, thereby limiting capital available for technology adoption. Nonetheless, we have not been able to find any paper that relates modern market participation, technology adoption and distance to markets.

Few papers have examined the impact of urban center size on farmers' market engagement. This is important because higher levels of urbanization have been linked to farm size, diversification, and price of land, variables that directly affect technology adoption (Masters, 2013, Rao et al. 2004). Current literature has mostly focused on how urbanization affects value chain transformation, especially concerning primary cities. These papers have made it evident that the rise of primary cities has speeded up the transformation of agricultural value chains, generating changes in actors, transactions and prices. For instance, Farina (2002) how the rise of

supermarkets in São Paulo and Rio de Janeiro restructured dairy and horticultural value chains, leading to changes in actor integration, product standards, and farmer modernization.

Absent in the literature are papers that look into the effect of secondary and tertiary cities on farmer decisions and dynamics. This is concerning with regards to market channel configuration and consumption for two reasons: (1) 75 per cent of the world's population lives in urban cities of less than 500,000 people (Cities Alliance, n.d.), (2) secondary/ tertiary cities encompass territorial spaces where there are strong rural–urban economic and social interdependencies (Tacoli, 1998).

It is important to note that, development literature has shifted from the traditional rural-urban dichotomy to examining differences in social and economic growth among deep rural areas, regions with secondary or tertiary cities, and metropolitan territories (Berdegué et al., 2016). This literature shows while larger territories generally exhibit lower poverty and social inequalities, secondary and tertiary cities vary in growth rates but play a crucial role in poverty reduction and warrant separate study (Kanbur, 2017). Theoretically, secondary cities may enhance economic growth by avoiding the congestion costs that larger cities face, suggesting urbanization thresholds where the benefits of larger cities diminish.

Finally, there are a few papers that study the effects of violence on technology adoption (though none through the modern market and technology adoption link). The overall idea is that violence acts as a transaction cost, that reduces the capital of farmers to invest (extortion and less demands for goods) as well as input availability (labor constraints due to forced immigration) which constraint technology adoption (Collier and Duponchel, 2013). In Colombia, Arias et al. (2013) showed farm investments are lower in more violent areas and, and Dinar and Keck (1997)

find that violence negatively impacts private investment in irrigation. Nonetheless, new papers have emerged in which the effects of violence are seen less as a shock on production and more on a change in farmer's behavior. Where a more violent environment leads to higher uncertainty, which encourages farmers to adopt technologies that will mitigate or reduce the risk of a violent shock. Still, it is unclear how modern market participation and urbanization levels interact with violence and its effects on technology adoption.

In this article we explore the participation of farmers in modern markets, and the subsequent effect on technology adoption, by analyzing how meso-level variables (including violence), access to value chains and territorial characteristics of secondary/tertiary cities and their catchment areas, and industrial organization, have an effect on farmers' market channel choice and on the decision of milk farmers to adopt 4 different technologies: (1) use a mix of pasture feed and concentrate, (2) use artificial insemination, (3) use fertilizer and herbicides and (4) use of cooling tanks. We contribute to the literature in 4 ways:

1. This article adds to the ongoing debate on farmer size by showing that smallholder farmers do participate in modern markets and adopt technology, though to a lesser extent than larger farmers. However, the difference in participation is relatively small.
2. We contribute to this literature by not only studying urban center size, but also focusing on secondary and tertiary cities and their catchment areas, which we will refer to from now on as rural-urban territories (RUT). These RUTs can also provide us with differences in urbanization thresholds, as we are able to see within each territory how market channel choice is affected by other meso and individual level variables. We show that higher urbanization levels positively impact modern market participation and technology

adoption. RUT size, processor density, and input store availability also affect these outcomes. Larger RUTs are more likely to participate in the modern market, with medium RUTs showing an 8-percentage point increase and large RUTs a 5-percentage point increase. Market participation boosts feed use, particularly in small and medium RUTs. Additionally, more processors at the RUT level significantly increase market participation, especially in small and large RUTs. Finally, RUT size affects technology adoption, with medium RUTs more likely to adopt artificial insemination and large RUTs more likely to adopt fertilizers and herbicides.

3. We also contribute to the literature on violence by showing that its effects on market channel choice are closely linked to urbanization levels and that different technologies interact with violence in complex ways. Specifically, while violence does not generally affect modern market participation, its impact varies by RUT size. In medium RUTs, violence increases the likelihood of using modern technologies like artificial insemination and feed, but in large RUTs, violence has a negative effect on both market participation and feed use. This suggests that violence disrupts local markets more severely in smaller, less diversified RUTs, while larger, more developed RUTs are better able to absorb these shocks.

In order to conduct this analysis, we use panel data collected in the Southwest region of Colombia in 2018 that contains recall information from 2013. This in itself is also innovative, as most papers that look at both market channel choice and technology adoption have focused on cross-section data. We focused on Colombia given its diversity in urbanization levels, farmer sizes and incidence of violence.

The paper will be divided into 6 parts, a brief background section on Colombia's milk market, a description of the different market characteristics, the data used, the conceptual model that will allow us to address the question stated above, a descriptive section, and finally some results and conclusions.

III. THE DAIRY SECTOR AND DAIRY POLICY IN COLOMBIA

Dairy is one of the most important sectors in Colombia, as it represents 24.3% of the agricultural GDP (Vega, 2018), making the country the fourth largest milk producer in Latin America. As well it's an important part of a Colombians diet as it is estimates that the population consumes three times the average of all other developing countries (Procolombia, 2016).

In the last thirty years, there has been an expansion of the modern milk market, especially to most rural areas of the country where both international and national modern firms have flourished, as a result of a reduction in the severity of protectionist tariffs that came with the signing of trading agreements in 2010. Nonetheless the sector is still highly protected, to the point that the government imposes quality and quantity standards for modern processors.

These policies have led to an almost clear separation between the modern milk markets and the traditional. The modern market is mostly composed of milk processors and some cooperatives. These actors take regular tests of the milk and pay farmers on average every two weeks and directly deposit within bank accounts. The traditional market is mostly composed by traders (also called jarreros or intermediaries), small stores (like bakeries), artisanal cheesemakers and directly to the consumers. Though they don't test the milk, they do weigh it, check for color and ask for vaccination records. They then sell the milk to local processors or individual households. These actors can be both from the region or travel to regions that are close to buy the milk.

i. General characteristics of the study region, the Southwest

The Southwest region is composed of six departments: Valle del Cauca, Cauca, Nariño, Putumayo, Caquetá, and Guaviare. Each is composed of municipalities (similar to “counties” in other countries); each municipality has a municipal capital city and other cities and rural towns. For the selection of departments for the survey, we would have chosen the universe of six departments but there was too much danger to conduct the survey in Cauca and Putumayo and so these were not selected.

The Southwest region is incredibly heterogeneous in many aspects including levels of urbanization, geographical aspects such as temperature, rainfall and altitude, and levels of violence and insecurity. All of these characteristics are suspected to be important in determining the level of value chain transformation. More importantly, this region has a high number of secondary cities and tertiary cities, which is the main purpose of this paper. This is key as this paper particularly focused on rural-urban territories (RUTS) as a determinant of value chain and technology adoption. Particularly, the Southwest is a mix of two departments with substantial urbanization with primary and secondary/tertiary cities (Valle del Cauca and Nariño), and two departments mainly populated by tertiary cities and rural towns (Caquetá and Guaviare).

Not only is the Southwest region heterogeneous in urbanization, but also within its on geography, a key factor in the type of breeds that used for milk production. The more urban and developed departments in our sample (Valle del Cauca and Nariño) have warm coastal areas and the rest is cool mountainous areas with fertile valleys good for dairy farming, especially for the European breeds. Caquetá and Guaviare (and Putumayo) have less favorable areas for pure dairy

production, but more suitable for dual purpose farming, consisting of low hot plains and the Amazon Forest.

With regards to production, this region has a mix of intensive (using supplemental feed) and extensive (using pastures only) farming, as well as a variety of small, medium, and large farms, as well as tropical and European cow breeds. There is a rough correlation between intensive farming using European breeds and the upland, and extensive farming using tropical breeds and dual-purpose cows (i.e., produce milk and meat rather than being specialized in milk) in the lowland and highland plateaus (Martínez et al., 2005); meaning the “most advanced” zones have a higher number of European breeds, whereas the intermediate has more mixed cattle. In this region, there are large international and national processors such as Nestle and Parmalat, and an even higher number of medium-sized processors and cooperatives, such as Colacteos and La Florida.

It is important to note that Colombia has had a 50-year conflict among right wing and left-wing guerillas, non-guerrilla criminal groups, and the military. This has generated substantial violence and insecurity in the Southwest region (and other regions). As well, since the 1980's there has been a sustained increase in organized crime that are linked to drug trafficking. However, the level of violence has differed greatly over the municipalities. Recently the greatest concentration of violence has been in the Cauca and Putumayo departments; we note below that we eliminated those from a potential sample of departments due to this violence. Nevertheless, in the four remaining departments violence was still an issue, yet extreme cases occurred but in a small subset of municipalities; the latter tended to be correlated with more hinterland and

mountain and jungle areas (usually far from the main dairy areas but sometimes mixed in with dairy farming areas).

The exertion of violence by these different groups varies in modality. There is physical destruction of property through explosives and land mines. As well there is deterioration of human capital through kidnappings and murders. Moreover, there is significant loss of capital through forced migration (to obtain land), increased extortions (higher than average taxes) and stealing of cattle. Affecting almost all aspects of production.

IV. DATA SELECTION

The data was collected for this paper in 2018, where 1,188 farmers were interviewed. The data collection followed two steps, first the selection of (nearly the full universe) of RUTs in the region, and then the selection of the farm household sample.

i. Selection of RUTs in the selected regions

The selection of RUTs in the Southwest region was as follows. Recall that the “RUT” (rural-urban territory) consists of a secondary/tertiary city (size between 15k-400k) and its immediate “market catchment area”, or functional territories. To identifying all the RUTs of a department we following the methodology presented in a paper by Fergusson, Ibañez and Hilliar (2018) and Berdegúe et al (2017), where we first divided the region by its department (equivalent to U.S. states), and then divided these based on functional territories. A functional territory is place where a certain group of people live and where they conduct most of their social life; more formally: spaces that contain a high frequency of economic and social interactions among its inhabitants, organizations and firms. These types of territories are not defined by administrative lines but by the intensity of social and economic relations. These functional territories’

boundaries were located using stable satellite night lights and census data that were determined by Berdegúe et al (2017). Once the functional territories were identified, they were categorized based on the size of their biggest urban center. Functional territories with city centers of more than 600k inhabitants were labeled metropolitan, 400k-600k: urban, 15k-400k: rural-urban territories (RUT), and those with less than 15k labeled rural. We focused only on RUTs, enabling us to disregard those completely rural territories, as well as primary city centered territories, in order to understand the effect of secondary/tertiary cities on value chain transformation within their market catchment areas. It is important to note that we had to forgo two departments given their high insecurity levels. We then selected the universe of 22 RUTs identified in the four departments but had to drop two during data collection because of high insecurity levels. It is important to note that because the catchment areas are focusing on social and economic relations, within the RUTs there is not only a secondary/tertiary city (the largest urban area in the RUT) but also there are rural towns and villages.

We expect the characteristics of the RUTs to differ over the size of the "anchor" city in each RUT. To explore this, we divided the RUTs into three sets. We refer to: (1) RUTs anchored by tertiary cities (15k-60k) as small RUTs; (2) by smaller secondary cities and bigger tertiary cities (60-120k) as medium RUTs, and (3) larger secondary cities (120k-400k) as large RUTs.

Selection of farm household sample

The farm household survey was based on a sample weighted by the number of dairy farms in the RUTs. To assemble a list of the universe of dairy farms per RUT, we used the National Dairy and Meat Account (Cuenta Nacional de Carne y Leche) and the Ministry of Agriculture's vaccination records per RUT; the latter represent 98% of dairy farms per RUT. Since this list

includes milk farmers as well as meat farms, we focused only on those who reported having milk production or farmers with a herd composed of at least 80% cows. We found that the total number of milk farmers in the selected RUTs was 27,415. Our budget permitted selecting a sample of 1,188 milk farmers, which were distributed over RUTs, roughly in proportion to the share of the RUTs in the universe of dairy farmers, but assuring that each RUT had at least 30 milk farmers. Next, in each RUT, we composed a list of all villages (veredas) with 10 dairy farms or more (to reduce travel costs for the survey) and eliminated farmers from the sample that did not live within these villages.

The 1,188 farm households were sampled proportionally to and randomly from the universe of dairy farms of the selected villages. The structured questionnaire was administered in-person to each household. The questions covered assets and behavior in the current (2018) and past year (2017), five years ago, and for certain variables, 10 years ago. The questions covered household characteristics, use and property of land, dairy production and processing, sales, soil management, purchase and use of concentrated feed, fodder, minerals, fertilizers, pesticides, and veterinary medicines; social and physical capital and exogenous shocks; and distances from the RUT main city and highways. For our analysis we are going to focus on the years of 2018 and 2013.

Finally, in order to control for the meso and geographical characteristics of each of the RUTs, we obtained information on the following: (1) urbanization; in this case we used a territorial survey that was undertaken in 2017 by Los Andes University to obtain the delimitation of functional territories through nightlights and census data. (2) Rainfall and temperature; used information published by the Colombian Environmental Ministry and (3) as well as violence index

that was composed of annual data on homicides, kidnappings, coca cultivation, forced immigration and number of terrorist attacks that came from police reports (4) number of milk processors and share of milk sold to the modern channel at the department level were obtained through the ASOLECHE (Association of Milk Producers in Colombia), the Ministry of Agriculture and the Chamber of Commerce for each of the territories.

V. DESCRIPTIVE STATISTICS

i. RUT characteristics

Table 1.1 presents meso-level and territorial characteristics of the different sized RUTs (i.e., size stratum of the anchor city) based on our farm household survey data, where we can highlight four major points.

First, though we selected the sample proportional to the universe of dairy farms of the selected villages, there seems to be a fairly balanced distribution of farmers across each type of RUT. This is expected given how ubiquitous milk farming is in Colombia.

Second, the highest percentage of farmers in high violence territories are located in small RUTs. This means that in our sample the small RUTs, are "taxed" by violence which, based on previous literature increases the costs and risk of accessing inputs, or selling milk, and even of peacefully farming.

Third, most farmers in small RUTs are in hot lowlands (where milk yields are also less) while most farmers in medium and large RUTs are in cooler areas. This is an advantage as cooler temperatures mean milk spoils less quickly post-harvest. This negative correlation between size and these agroecological factors is due to the historical (from Spanish colonization) urban

settlement patterns that favored the cooler and less diseased uplands and highlands (Zambrano and Bernard, 1993). It is also clear that rainfall varies greatly across RUTs and within them. Rain can have both negative and positive effects, on the one hand more rain means more nutritious grass, but too much rain can cause floods and rotting of the pastures.

Table 1.1: Meso-Level and Territorial Characteristics by RUT

Types of RUTs	Small RUTs	Medium RUTs	Large RUTs	Total
Meso Level and Territorial Characteristics				
Share of farmers	37	33	30	100
Violence Index				
% of farmers in high violence RUT (index >0)	69	37	6	40
% of farmers in moderate violence RUT (Index - 0.25<x<0)	16	2	21	13
% of farmers in low violence RUTs (Index <- 0.25)	15	62	72	47
Average rainfall (mm/month)	171	67	122	122
	(61)	(6.3)	(73)	(70)
% farmers in cold areas (< avg 20°C)	32%	97%	80%	67%
% farmers in hot areas (>avg 20°C)	68%	3%	20%	33%
Average number of modern milk processors and processing plants per municipality (in 2018)	1	1	5	2
	(2.2)	(0.6)	(4.5)	(3.4)
Average number of modern milk processors and processing plants per state (in 2018)	15	16	17	16
	(8.1)	(5.1)	(6.2)	(0.4)

Standard deviation in brackets

Source: Authors' own survey

Fourth, the number of modern milk processors and processing plants is on average higher in larger RUTs. This is probably related to the fact that larger urban centers are able to host more plants and processors. Still, as table 1.1 shows, the jump in the number of processors is only in the largest of RUTs meaning that this relationship is not completely linear. This phenomenon might be further explained by the number of modern processors at the state level. If medium RUTs are located near larger ones, then there might not be the need to establish new processing plants or collection centers in these territories.

Table 1.2 shows farm household characteristics by RUT size stratum. From this table that are four major observations. First, there is a U-curve relation of herd size and farm size on the one hand, and the size of the RUT. Small RUTs (anchored by tertiary cities and rural towns) tend to have large dairy farms surrounding them (with few small farms) while medium RUTs have smaller farms. Then large RUTs (similar to small RUTs) also have larger farms but also a higher dispersion of farm sizes (hence small and larger farms coexisting in large RUTs). This may reflect a bimodal pattern of milk yields over large farms. In areas with less access to supplementary feed and cattle breed suitable for production, it is necessary to have a large herd to compensate for the low milk yield per cow.

Second, the average distance for farmers to reach the anchor city, the nearest modern milk processor and agro-input stores is consistently highest in the small RUTs. This implies that there is a strong correlation between anchor city size and the ease of access of farmers to infrastructure and market facilities.

Table 1.2: Farmer level characteristics by RUT sizes

Types of RUTs	Small RUTs	Medium RUTs	Large RUTs	Total
Farm Capital				
Average size of herd (# cows)	29 (45)	6 (8)	11 (28)	16 (33)
GINI of cattle	0.573	0.505	0.671	0.66
Average size of pastures (ha)	55 (32)	6.1 (42)	19 (25)	28 (30)
% of land owned by farmers	94 (0.2)	90 (0.3)	89 (0.3)	91 (0.3)
Non-Farm capital				
Non-farm capital Index	2.1 (1.7)	2.2 (1.7)	2.5 (1.9)	2.2 (1.8)
% of farmers that own car/motorcycle	12	22	11	15
% of farmers that are part of an association	40	50	32	41
Household characteristics				
Average Age (of head of farm)	52	56	57	55
Gender (% of head of farm that are female)	16%	19%	19%	18%
Schooling (% of head of farm)				
None	8%	8%	5%	7%
Primary	73%	78%	79%	76%
High school	17%	14%	13%	15%
University-technical	2%	1%	3%	2%
Graduate school	0%	0%	0%	0%
Farmer Distances				
Average distance to anchor city (minutes)	29 (39)	23 (16)	24 (37)	26 (33)
Average distance to nearest modern milk Processor (minutes)	29 (1.3)	20 (0.8)	24 (1.5)	24 (1.3)
Average distance to agro-input stores (minutes)	29 (37)	22 (17)	23 (37)	25 (32)

Standard deviation in brackets

Source: Authors' own survey

Third, the share of farmers that are part of an association is lowest in large RUTs (about 30%) compared to small and medium RUTs with about 50% and 40% respectively. This reflects

the importance of associations in areas with poorer infrastructure. For example, associations, in general, provide transportation to farmers. Thus, if distances are longer in smaller RUTs, then the need for transportation is higher and thus likely to increase interest in association membership.

ii. Marketing Channels

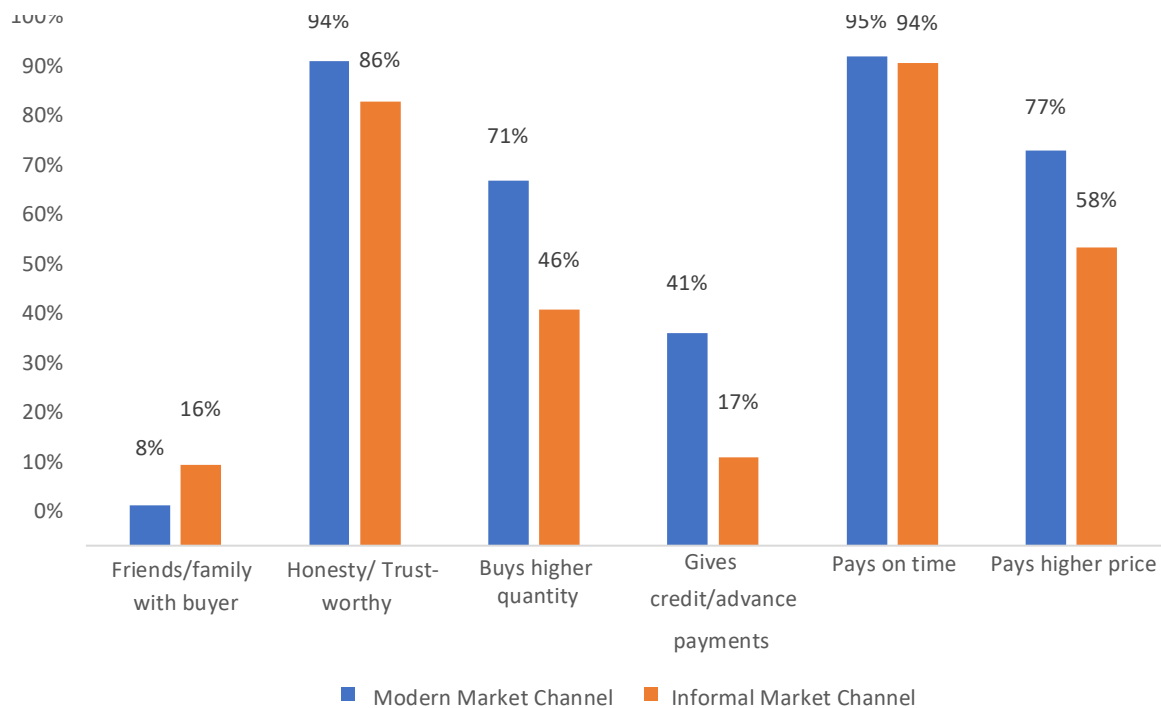
Most sales in 2018 were done through the traditional channels: 78% of households sold their milk directly to consumers or to traditional milk traders and processors. Only 22% of the households sold through the modern channels, and within this group 71% sold to processors and 29% sold to cooperatives.

In general, there are no contracts between milk producers and any of the market channels. For this reason, it is possible that a farmer sells to two different channels within a year. Nonetheless, most farmers tend to stay within one market channel, only 2% of farmers reported selling to two different sellers, and only 0.3% sold to both modern and traditional channels. We believe this phenomenon occurs because it is costly to change channels, as they would need to find a new buyer and negotiate price and quality. As well, farmers have already built a new relationship with their buyers and are aware of their consistency in payment and their transportation abilities.

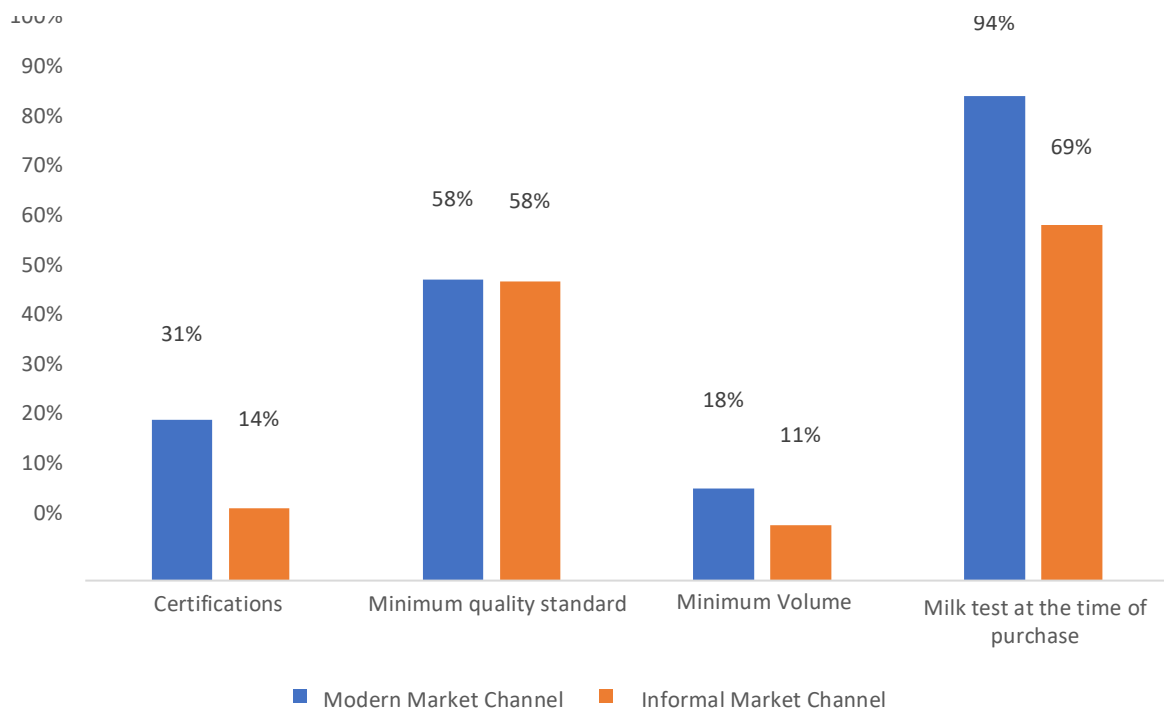
Figure 1.1(a) reflects specific reasons, related to trust and procurement characteristics, for buyer selection. Farmers were asked why they chose to sell to each channel and were given multiple answers which they could choose from. In particular, 94% of farmers that sell to the modern market and 85% of farmers selling to the traditional market channel stated that honesty/trustworthiness was an important reason for buyer selection. This high level of trust indicates that there are more complex reasons in choosing the modern channel.

Figure 1.1: Market channel benefits and requirements

(a). Share of farmers in 2018 that indicated the specified reason for selling to their current market channel



(b). Share of farmers in 2018 that indicated the requirements each channel imposed



Source: Authors' own survey

Prices seems to be an important factor in selection of a market channel, especially in choosing the modern market. In figure 1.1, 77% of modern market milk suppliers selected “Pays a higher price” as a reason for choosing this channel, a share almost 33% higher than that of traditional milk suppliers. This is consistent with the information from table 1.3, where the average price for a liter of milk is higher (significantly) for the modern milk channel in every season.

In figure 1.1(b), we can see that the requirements imposed by the modern market channel are higher than those in the traditional market. The difference is particularly stark in the testing of the milk at the time of purchase, where 94% of farmers that sell to the modern market stated the milk was tested, where this share was 69% for the traditional market. From interviews with key actors within milk processing, it became clear that what is needed is high quality milk (measured by fat and solid content), sanitary standards and consistent volume throughout the year. This is consistent with the graph as quality and testing seem to be the biggest requirements for all channels.

In table 1.3 we can see the price differentials across each type of market channel. Interestingly, though the modern milk market pays higher (869 COP/lit vs 811), 58% of traditional milk suppliers stated “higher prices” as a reason to choose this market channel. Given that the traditional channel does not test milk quality (beyond just weighing it), it is possible that farmers actually get a higher price for lower quality milk in the traditional channel than they would in the modern market channel. Additionally, we see in table 1.3, more farmers reported their milk being picked up by the traditional market than those within the modern milk market. Farmers stating that the traditional channel pays higher price might also be taking into account transportation

costs, as the modern channel discounts these. In table 1.3 we can see that the traditional channel provides more transportation on average, which would result in a reduction in transportation costs for these farmers.

Table 1.3: Average price per liter of milk and share of farmers that reported milk being picked up by market channel in 2018

Type of Market	Modern Milk Market	Traditional Milk Market	T-test for significance of differences (F statistic)
Average price (CO peso)/lt			
Wet Season	869 (223)	811 (205)	3.93***
Dry Season	892 (202)	869 (203)	5.63***
Total	869 (223)	811 (204)	3.93***
Market channel provides transportation	74%	86%	4.74***

Standard deviation in brackets

* Significant at P=0.10; ** significant at P=0.05; *** significant at P=0.01

The conversion rate in 2018 was around 2957 COP/ USD

When looking at non-price factors, timely payments emerge as an important reason of buyer selection for 95% of modern market milk suppliers and 94% of traditional milk suppliers. Other important reasons are buying a higher quantity of milk, and providing payments in advance. Surprisingly, having a friend/family member as a buyer is not an important reason behind choosing a market channel, which means farmers are selecting based on pricing and procurement characteristics rather than familiarity with the buyer.

Surprisingly, rainfall is only slightly different amongst the two groups of suppliers. Generally, harsher dry seasons lead to a fall in the quality of grass, which also decreases the

quality and quantity of milk. As table 1.3 shows, there is a slight increase in prices during the dry season as processors, especially modern market processors, are willing to pay higher prices given the decrease in milk availability.

Table 1.4 presents statistics on the market channel choice according to different meso-level and territorial characteristics. A first observation is that there is no complete exclusion of the most rural farmers from the modern milk market. In general, almost 28% of farmers selling to the modern milk market reside in small RUTs. Still, when comparing the traditional and the modern milk market, it seems farmers residing in medium and large RUTs make up a higher share within the modern milk market (72%) compared to the share supplying the traditional milk market (61%). These descriptive statistics suggest that as urban centers grow, more milk farmers choose the modern milk market.

Secondly, though farmers in high violence RUTs sell to both channels, the traditional channel is made up of a higher proportion of traders that live in high violence areas. While 41% of farmers selling to the tradition market are located in high violence RUTs, this compares to 33% among farmers selling to modern milk channel. This is not surprising as the traditional milk market is in partly composed of local traders. Farmers in small local areas are probably more inclined to sell to a known trader than a possible stranger.

A third observation is that, on average, there is a higher agglomeration of milk processors (at the state and municipality level) for farmers that sell to the modern milk market. In table 1.4 we see that the average number of modern milk processors in 2018 for modern milk market suppliers is 4, while the number is 3 for traditional milk market suppliers and these means are statistically significantly different. In addition, the average share of milk sold to the modern

channel within a state is 46% for the sample of farmers selling to modern milk suppliers compared to 42% for those selling to the traditional market.

Table 1.4: Meso-Level and Territorial Characteristics by Market Channel Choice

Type of Market	Traditional Milk Market	Modern Milk Market	Total	T-test for significance of differences (F statistic)
Meso Level and Territorial Characteristics				
Rural-Urban Territories (by inhabitants)				
% of farmers in Small RUT (15k-60k)	39	28	37	4.2***
% of farmers in Medium RUTs (60k-120k)	32	39	33	-2.9***
% of farmers in Large RUTs (120k-400k)	29	33	30	-1.49
Violence Index				
% of farmers in high violence RUT (index >0)	41	33	39	2.6***
% of farmers in moderate violence RUT (Index -0.25<x<0)	13	12	13	0.91
% of farmers in low violence RUTs (Index <-0.25)	46	55	47	-3.26***
Average rainfall (mm/month)	121 (69)	122 (75)	121 (70)	-0.33
Average number of modern milk processors per municipality (in 2018)	3 (3)	4 (4)	4 (3)	-4.19***
Average share of milk sold to modern milk channels (state wise)	42 (18)	46 (18)	43 (18)	-4.62***

Standard deviation in brackets

Source: Authors' own survey

* Significant at P=0.10; ** significant at P=0.05; *** significant at P=0.01

Table 1.5 depicts farmer level characteristics, including their technology use by market channel choice. Three important points emerge within the farm level characteristics; first, a big share are farmers are small or micro (68%), and in both the traditional or modern (70% of traditional and 54% of modern). However, the type of farmers (based on herd size) that structure each of the markets is different. The traditional market has a higher share of micro farmers, and the modern milk market is composed by a higher share of medium and large farmers.

Secondly, most farmers own their land, and on average modern milk suppliers own slightly more of their land, as the difference between in mean is only 3%, but it is still significant. This is surprising given the number of farmers that live within high violence areas, where insurgent groups have been known to take away lands and forcibly displace farmers, generating a problem within land tenure. This only indicates that the effects of violence are more complex than just the effect on land ownership.

Third, we see that a higher share of farmers selling to the modern market are in an association (54%) compared to those selling to the traditional market (39%). This probably reflects the value of the coordination role provided by associations for farmers to sell as a united front to the modern market channels. They also help monitor input uses, quality measures and can negotiate better prices.

Fourth, the average time it takes farmers to reach the anchor city, the closest modern processor and the closes agro-input stores is slightly less for modern milk market suppliers, but the difference is substantially less than the difference in the composition based on RUT size (see table 1.4). This initially tells us that the size of an anchor city is more of a determinant on market channel choice than distance to urban markets.

Table 1.5: Farmer level characteristics by market Channel Choice

Type of Market	Traditional Milk Market	Modern Milk Market	Total	T-test for significance of differences (F statistic)
Farm level assets				
Heard size				
% of micro farmers (<5 cows)	29	13	26	5.7***
% of small farmers (5-19 cows)	41	41	41	-3.9***
% of medium farmers (20-49 cows)	15	24	17	-2.4**
% of large farmers (>50 cows)	15	22	16	-0.48
Average share of land owned by farmers	91 (28)	94 (24)	91 (24)	-1.8**
% of farmers that own car/motorcycle	39	54	42	-5.4***
% of farmers that are part of an association	12	29	15	-8.7***
Farmer Distances				
Average distance to anchor city (minutes)	26 (33)	24 (32)	25 (32)	0.63
Average distance to nearest modern milk Processor (minutes)	24 (32)	22 (27)	24 (31)	1.58
Average distance to agro-input stores (minutes)	25 (32)	23 (27)	25 (31)	0.87

Standard deviation in brackets

Source: Authors' own survey

* Significant at P=0.10; ** significant at P=0.05; *** significant at P=0.01

iii. Technology adoption

The modern milk market needs milk with 3 specific traits: 1. High quality: measured by the percentage of fats and solids within the milk; 2. Consistent quantity throughout the year; 3. Sanitation standards: measured by the percentage of bacteria as well as no traces of antibiotics within the milk. Higher levels in any of these traits enables a farmer to get a higher price.

In order to achieve these traits farmers can update their technologies in 4 areas: feeding, reproduction, pasture management and sanitary practices. Better feed increases dry matter intake (DMI) which leads to an increase in milk production and quality (Hills et al, 2015). Different studies have shown that just by mixing pasture feed with concentrate feed (especially if it is made by a starchy product) can increase milk yield and quality (measured in protein percentage) by at 25-30% (Griinari et al. 1997 and Mackle et al. 1999). This leads not only to higher quality milk but also allows milk to be produced consistently around the year. Better reproduction practices, such as using artificial insemination not only allows farmers to create a herd that is better suited for their surroundings, but also allows the reproduction cycle to occur year-long, ensuring that the cows are always producing milk. Pasture management increases the quality of grass (DMI) needed for milk production and quality, as well as preventing sickness in cows from ingestion of poisonous weeds and harmful bugs. Better sanitation practices lead to less bacteria within the milk, and the prevention of diseases that can lead to the use of antibiotic. This particular area can include different practices such as cleaning milking cans, correct udder treatment when milking and the use of milk tanks. Keeping the milk cool not only slows down bacteria growth but also prevents milk degradation that can lead to less percentage of fat.

Table 1.6 depicts the feeding, reproduction and sanitary practices of farmers within each market channel. Overall, we find that the adoption of practices associated with higher milk quality is more prevalent among farmers selling to the modern market compared to their counterparts selling to traditional markets.

For feed practices, almost 60% of those selling to the modern market use concentrate compared to about 50% for the traditional and the average concentrate per cow used in the

modern market is almost double that used in the traditional market. However, the use of concentrate is generally low in the study sample. On average, grass fed milking cows should be receiving between 3-6kg concentrate daily (Wernli K, 1984), yet, in our sample only 53% of farmers are actually feeding concentrate, and the average quantity of concentrate used by these farmers is 0.86 kg/cow/day.

For pasture management we consistently see higher technology use among farmers selling to the modern market. For example, 53% and 17% of farmers selling to the modern market channel use fertilizer and herbicides compared to 35% and 13% of their counterparts selling to the traditional channel. In addition, the share of farmers using both fertilizer and herbicides (important complementary inputs for pasture management) is three times higher among those selling to the modern market channel (11%) compared to those selling to the traditional market (3%).

Within sanitary practices, while the practice of washing milk cans before milking is common among all farmers irrespective of their market channel (97%), the use of all other sanitary practices is higher among farmers selling to the modern market channel. For example, while 16% of farmers selling to the modern market channel use cooling tanks, no farmers selling to the traditional market use these tanks. This is probably due to the fact that many modern processors rent out cooling tanks to their suppliers (paid by the farmer). It is surprising that only 4% of farmers in the sample use cooling tanks as it preserves the quality of milk in a country that has many regions with high temperatures.

Table 1.6: Technology adoption across market channel choice

Type of Market	Traditional Milk Market	Modern Milk Market	Total	T-test for significance of differences (F statistic)
Feed practices				
% of farmers that use concentrate	51	58	53	-2.4**
Average kg concentrate/cow/day	0.74 (1.5)	1.41 (5.3)	0.86 (2.7)	-4.5***
Pasture Management				
% farmers that use fertilizer	35	53	39	-5.6***
% farmers that use herbicides	13	17	14	-2.26**
% farmers that use any of these	45	63	49	-4.9***
% farmers that use fertilizer and herbicide	3	11	5	-4.8***
Reproduction Management				
% of farmers that use artificial insemination	10	24	13	-8.0***
Sanitary practices				
% of farmers that use milk cooling tanks	0	16	4	-12.3***
% of farmers wash milk cans before milking	97	97	97	-0.093
% of farmers use disinfectant for udders	32	51	36	-5.7**
% of farmers visual mastitis test	47	65	51	-4.9**
% of farmers that seal teats after milking	34	54	39	-5.9**
% of farmers that use disinfectant, seal and visual mastitis test	18	38	21	-7.1**
% of farmers that use mechanic milking parlors	2	12	4	-7.7***

Standard deviation in brackets

Source: Authors' own survey

* Significant at P=0.10; ** significant at P=0.05; *** significant at P=0.01

We also find differences in sanitation practices related to the handling of cows. While using disinfectants for udders, visual mastitis tests and sealing teats after milking are used by

51%, 65% and 54% respectively, these are only used by 32%, 47% and 34% of farmers selling to the traditional market respectively and these mean differences are statistically significantly different. When looking at the use of multiple sanitary practices there is a clear difference across the different market channels. The share of farmers selling to the modern market that use multiple practices is more than double those selling to the traditional market. While 38% of farmers within the modern channel disinfect, seal and do visual mastitis tests, only 18% of farmers that sell to traditional markets that do all three practices (Table 1.6).

VI. EMPIRICAL STRATEGY

i. Market Channel choice

To estimate farmers' modern market choice, we assume the following unobserved panel data model specification:

$$m_{it} = L_{it}\beta_L + LV_i\beta_{LV} + X_{it}\beta_x + \gamma_t + c_i + \varepsilon_{it}, \quad [1]$$

Where m_{it} is the binary indicator of modern market channel choice for farmer i in time t and is equal to =1 if farmer i sells any of their milk to the modern milk market and 0 otherwise. L_{it} is a vector of time-variant meso-factor variables (at RUT level) such as an index of violence, average monthly rainfall and the density of modern milk processors measured as the number of modern processors and processing plants at the RUT and department level. LV_i is a vector of time-invariant meso-level variables such as the size of the RUT and distance to nearest town and nearest modern milk processor. We also include the interaction between RUT size and violence index to account for any relationship between the incidence of violence and level of urbanization (especially if more rural communities have less access to social infrastructure). X_{it} is a vector of individual farmer characteristics that includes farmer age, gender and education level as well as

variables to capture farmer wealth (land and non-land assets), and social capital (e.g. membership in an association). β_L , β_{LV} and β_x are the coefficient estimates associated with the study covariates to be estimated. γ_t , are year fixed effects which are included as time dummies and ε_{it} is the error term which we assume is distributed: $\varepsilon_{it} | \mathbf{L}_{it}, \mathbf{LV}_i, \mathbf{X}_{it}, c_i \sim \text{Normal}(0,1)$. The term c_i captures time invariant unobserved farmer-specific factors, which we assume has the following characteristics:

$$c_i = \psi + \bar{L}_i \xi_L + \bar{X}_i \xi_x + a_i \quad [2]$$

$$a_i | L_i, X_i \sim \text{Normal}(0, \sigma_a^2)$$

Where $\bar{L}_i$ and $\bar{X}_i$ are the means of the time variant individual and farm-level characteristics.¹ Additionally, we assume that c_i is conditionally distributed $c_i | \mathbf{L}_{it}, \mathbf{LV}_i, \mathbf{X}_{it} \sim \text{Normal}(\psi + \bar{L}_i \xi_L + \bar{X}_i \xi_x, \sigma_a^2)$.

Overall, we expect that higher levels of urbanization have a positive effect on the probability of choosing the modern market channel. Urban centers can strengthen rural-urban linkages by providing specialized goods and services, increase social and economic interactions, have better infrastructure that connects communities nationally and internationally and makes public and government agencies more available. All of these characteristics can make it easier for farmer to access the modern channel as they can more easily compare prices, negotiate between firms within the modern channel, and more easily transport and test their milk. Nonetheless, there is a possibility that very big urban centers can have a negative effect on market channel choice as there can be a trade-off between congestion costs and economies of scale. Larger

¹In this paper, we adopt a class of CRE models developed by Mundlak (1978) and Chamberlain (1980) that allows for the modeling of the distribution of the omitted variable (c_i) conditional on the means of the included strictly exogenous variables ($\bar{x}_i$) rather than treating the omitted variable as a parameter to estimate.

centers can have increased transportation times due to more vehicular congestion, making it harder to access processors that are on different neighborhoods. This could make the traditional channel more attractive as they offer transportation at a higher rate than the modern channel.

As noted earlier, it is expected that farmers with larger farms and those that are closer to paved roads and cities and processors will find it easier to access the modern market channel compared to small farmers and those further away. Additionally, we expect that having one's own transportation, as well as being part of an association or cooperative increases the probability of selling to the modern market. Being able to deliver the milk makes it easier to sell to processors of all sizes; and being part of a cooperative means small farmers can produce jointly with other farmers and gain access into modern markets. Furthermore, we assume that a higher density of modern processors within an area positively increases the probability that a farmer sells their milk to modern processors as farmers are able to negotiate and overall receive higher prices.

With regards to violence, the effect on market channel participation remains unclear. On the one hand violence can reduce production and safe transportation, making it harder to sell to the modern channel. However, the modern channel offers more access to credit and pays higher prices (see table 1.3), meaning that the modern channel can serve as a way to mitigate risk caused by violence and conflict. In addition, the modern channel (by having a more recognizable name) can evoke confidence in areas where farmers are unsure to trust. Cassar, Grosjean and Whitt (2013) show that in areas with higher conflict there is a deterioration of local social relations, where victims are less willing to participate with actors they do not know, but have more trust in others living farther away from the subject. In this sense, in territories with larger urban centers,

higher levels of violence can make the modern channel more attractive as they are known customers while local traders can be strangers given the bigger size of the city. In smaller areas, it is more probable that farmers know the local traders and have some that they can trust. Additionally, in smaller urban areas there is less presence of big processors, meaning that interactions with them can signal higher levels of income and increase farmers risk of being targeted. For this reason, we include the interaction between violence levels and RUT size.

Considering age and education as proxies for experience and ability to navigate more stringent market requirements (respectively) in a culture where males are usually more economically empowered, we expect that older, male and more educated farmers would be more likely to sell to the modern market.

To estimate the parameters in equation [1] we use a correlated random effects probit (CRE probit) model using pooled maximum likelihood estimation-MLE. This model allows us to estimate probabilities of selling to each market while controlling for unobserved farmer-specific heterogeneity ((Wooldridge, 2010). The CRE probit model also allows us to estimate parameters for our time constant control variables (e.g. farmers that have always chosen the modern market channel and variables such as the size of the RUT).

Thus, we empirically model the probability of famer i choosing to sell to a specific market j (where j=1 if modern market is chosen and j=0 otherwise) in time t (two time periods of 2018 and 2013) conditional on farmer and RUT characteristics in the general form of equation 3 below:

$$\Pr(y_{it} = 1 | X_{it}, L_{it}, LV_i) = \Phi(L_{it}\beta_{La} + LV_i\beta_{lva} + X_{it}\beta_a + \gamma_a + \psi_a + \bar{L}\xi_{La} + \bar{X}_i\xi_{xa})$$

t=1,2 [3]

Where the α subscript reflects that a parameter vector has been multiplied by $(1 + \sigma_\alpha^2)^{-1/2}$. Since we are using a probit, we assume the distribution of Φ to be the cumulative distribution function of the standard normal distribution. The CRE probit using joint MLE yields scaled versions of β , ψ , and ξ , and we are able to relax the conditional independence assumption and obtain standard errors that are robust to arbitrary serial correlation. We obtain the average partial effects of the individual and farm-level characteristics as well as meso-level and territorial characteristics.

Additionally, we run similar regressions for each of the RUT, while maintaining the same right-hand variables (except the interaction between RUT and violence). This will allow us to understand how the covariates vary within each type of territory.

ii. Technology use

To understand the determinants of technology use, conditional on market channel, we explore the farmer's decision to adopt various technologies associated with higher milk quality (nutritional quality and safety). These include feed, artificial insemination, fertilizer and herbicide, and cooling milk tanks. Particularly, we focused on if the trader used this technology in the last year (at any time during 2018 and 2013). As noted earlier, the modern channel offers a price premium for milk with these characteristics. In some cases, the modern market channel helps disseminate the benefits of these technologies or supports farmer access to them (e.g. some modern processors lease cooling tanks). For this reason, we are expecting that participating within the modern market will have a positive effect on the decision to adopt each of these technologies, though the effect is likely to vary with other farmer and meso-level factors.

Though we are measuring all technology use within each time period, it is important to note that not all technologies have the same effect on quality and quantity. Feed type and the use of cooling tanks have an immediate effect on the quality, quantity and safety measures of milk. This makes it easier for the market channel to respond with higher prices. However, artificial insemination and fertilizer and herbicide use are longer-term investments, meaning that the effect on quality and quantity can be delayed. This in turn means that the price compensation can also be delayed, potentially reducing the effect that selling to the modern channel in a particular time period might have on these types of technologies. However, because we note that farmers tended to not switch from one channel to another or sell to multiple channels (over the survey period), we consider farmers use of these practices as likely reflecting their expectations about the opportunities available to them in the different market channels.

An important contribution of this paper is exploring the extent to which meso-level factors (such as RUT characteristics) and violence affect technology adoption among dairy farmers. Overall, we expect that higher levels of urbanization increase the probability of technology adoption. In general, we know that larger urban areas there is more knowledge distribution and availability of specialized goods and services, making it easier for farmers to access the technology and information on how to use it. Nonetheless, in too big of a territory, congestion can make it harder for farmers to access the correct information or make transportation of certain inputs (like artificial insemination) harder given. This could then lead to a lesser adoption of a technology.

With respect to violence, the effect of violence on technology adoption is ambiguous and likely to vary significantly across technologies. From literature, we know that violence and conflict

overall reduce production through a decrease in productive capacity and deterioration on human capital, so farmers can try to mitigate the risk of lower production through adoption (or non-adoption) of technologies. On the one hand, farmers could increase the use of technology adoption to account for the anticipated fall in productivity, and overall reduce the size of the damage. On the other hand, if farmers anticipate a decrease in production, they could potentially decrease technology adoption as it signifies higher costs.

With respect to technology types, Arias, Ibañez and Zambrano (2019) introduce the concept of technologies that are complementary to violence, i.e. can increase the risk of violence. For example, farmers may invest in mobile assets to minimize the risk of forced migration, or decrease their investment in large physical assets, as this may signal household wealth which can make them a target. Farmers may also choose investments that are more easily recoverable than those which would take more time to recover. Thus, a farmer might choose non perennial crops over perennial crops, (even though perennial crops are more profitable) because if they are destroyed, it will take less time to plant the non-perennial crops again and see results compared to perennial crops.

This paper explicitly explores the effects of violence on the use of feed, artificial insemination practices, cooling tanks, fertilizer and herbicides. We categorize these investments in four ways to distinguish the potentially heterogeneous effects of violence: (1) by the length of the investment (i.e. how long it takes to see increases in productivity), (2) the sensitivity of the investment to shocks (e.g., how easy it is for the farmer to recover if these are destroyed) and, (3) if they can be an asset liability (e.g. asset that signals that the farmer has a higher wealth and thus is a better target for extortion), (4) the investment's complementarity to conflict shocks

(e.g., if the farmer loses land, cattle or labor would the adoption of this technology exacerbate the impact of this shock). For example, the use of concentrate is a short- term investment, with medium sensitivity, and low asset liability. The concentrated feed quickly increases milk quantity and quality and is easily given to cattle. The destruction or unavailability of feed (for example by roadblocks that prevent its distribution) will have a quick negative effect on milk production, but the use of feed concentrate can easily be restarted without a critical effect on the cows since they will always have pastures. In addition, feed has a low asset liability as it does not signal higher wealth, and can be transported more easily if the farmer needs to move quickly due to a violence outbreak. If a farmer's land were reduced or some cattle stolen, feed concentrate would help supplement pasture feed and maintain/ increase milk productivity. There might be some reduction in overall feed use if labor availability is reduced (labor is needed for feeding the concentrate) or increases in price due to roadblocks.

Artificial insemination signals that a farmer is trying to build a herd that is better adapted to its environment and can consistently produce more and better milk. In the model, artificial insemination is measured as binary variable that indicates if the farmer used the technology in each timer period or not (independent if it was used on all the herd). The productivity results of using artificial insemination are a medium-term investment as the farmer needs to wait for the calf to be born and grow. The effect of violence on the adoption of this technology is ambiguous. Transporting and applying artificial inseminations requires labor and adequate storage, which are both susceptible to violence. In addition, if the cows resulting from insemination are killed or stolen, it will take the farmer at least 2 years to breed another animal. However, cows that have better genetics sell faster and for a higher price, making it easier for farmers that are displaced

off their lands. While having a breed from artificial insemination might make the farmer a target, it is difficult to distinguish better genetics without expertise in the field. Facing a reduction in pastureland, a better herd can potentially adapt better to the reduction in pastureland.

Fertilizer and herbicide are used to increase the nutritional content of grass so that cows produce more and higher quality milk. This specific technology can be considered a medium level investment, as the pastures need time to grow. The adoption of this technology will most likely be negative to higher violence levels. Disruptions in transportation can delay the application of fertilizer and herbicide which can ruin the investment. Destruction and displacement of land again will render the investment worthless as it will take at least a year to rebuild the pasture (if not more). As well, this technology is sensitive to rainfall and weather, making it even more susceptible to other shocks.

The effect of violence on cooling tanks is also ambiguous. On the one hand, if violent shocks affect the transportation of milk (road closures or imposed curfews) then milk will be less susceptible to spoil. On the other hand, milk coolers are harder to transport, are very expensive and hard to sell. As well they can be seen as a liability, as they can indicate to the farmers wealth or farm size. Nonetheless, many milk coolers are rented or shared by a community, making it easier for farmers to stop using them if they needed it.

The relationship between violence and urbanization is also ambiguous. On one hand easier access to inputs and agricultural markets (where they can more easily sell their cows) can increase adoption of technologies that will reduce risk. On the other in larger urban areas there can be distrust of local input sellers (as they are not directly known to the farmer) which can then deter farmers from adopting a specific technology.

Finally, we explore the role of farmer socioeconomic variables on technology adoption. With regards to size, while smaller farmers can more easily apply certain technologies (i.e. artificial insemination, as it is easier to monitor the cycles of 5 cows than 30) than medium farmers, larger farmers have economies of scale. With regards to cooling tanks, given that these are mostly used for large quantities of milk small farmers might not be inclined to use them. Access to social and physical capital most likely increase the use of technologies as farmers can more easily access the inputs and information needed. The one technology where the results are ambiguous is the use of cooling tanks, on the one hand many associations help farmers to consolidate their milk with others, making it unnecessary to buy or rent a cooling tank. On the other, smaller farmers can form an association and together rent the cooling tank together.

VII. EMPIRICAL APPROACH

To estimate the effect of market channel choice on technology adoption we assume the following panel data unobserved model specification:

$$y_{it1} = m_{it}\varphi + L_{it}\beta_L + LV_i\beta_{LV} + X_{it}\beta_x + \gamma_t + c_i + v_{it} \quad [4]$$

Here, y_{it1} is the technology (e.g. average kilograms of feed concentrate used per cow per month or the use of AI) while m_{it} , as established in equation [1], is a binary variable that represents whether the farmer is selling to the modern market channel ($m_{it}=1$) or not ($m_{it}=0$). L_{it} is again a vector of time-variant meso-factor variables (at RUT level) that includes an index of violence, average monthly rainfall, and the density of agro-industrial supply stores. LV_i is a vector of time-invariant meso-level variables that includes RUT size, distance to agro-industrial supply stores and distance to the nearest towns. We also include the interaction between RUT size and violence index to take into account the relationship between these two variables. X_{it} is the vector

of individual farmer characteristics, farmer age, gender and education level, land and non-land assets and social capital. γ_t are year fixed effects, φ is the average effect of market channel choice on feed use and β_L , β_{LV} and β_x are the average effects of the farm and territory related covariates. v_{ijt} is the error term assumed to be normally distributed. As before, c_i are the unobserved farmer-specific effects that have the following characteristic:

$$c_i = \psi + \bar{L}_i \xi_L + \bar{X}_i \xi_x + a_i \quad [5]$$

$$E[a_i | X_i, L_i] = 0$$

Our key variable of interest, m_{it} is potentially endogenous. This is because a farmer's decision to sell to the modern market channel could be correlated with unobserved farmer characteristics that could affect both their market channel choice and their input use. For example, more progressive and well-connected farmers might be more exposed to and able to engage with modern milk processors but also more likely to use modern inputs generally. To address any endogeneity due to any unobserved farmer characteristics, we will use an instrumental variable correlated random effects approach (IV-CRE). Following Wooldridge (2010), the IV must satisfy both the relevance condition (i.e. be strongly correlated with the endogenous variable) and the exclusion restriction condition (i.e. its only effect on the outcome variable of input use should be through its effect on the endogenous variable). For this study the number of modern processors and processing plants within the RUT is used as an instrument. We argue that this variable is related to market channel choice as a higher number of actors from a specific channel can influence farmers to sell to that specific channel as well. Secondly, the number of milk processors within an RUT should not directly affect the farmer's decision to choose the type of feeding scheme used, especially since modern processors do not supply

farmers with feed inputs. Thus, we argue that conditional on our set of farmer and territorial control variables our instrument is reasonably exogenous. Our approach and selected IV are consistent with several studies that have examined the effect of cooperatives and market channels on farmers' behavior and welfare (Nuhu et al 2021, Ma and Abdulai 2016, Zang et al 2020, Ma et al 2021, Jimenez et al 2018). Thus, the estimating equation for estimating the impact of modern market channel on concentrate use is:

$$y_{it} = Z_{it}\beta_j + \gamma_t + \psi + \bar{Z}_i\zeta + a_i + v_{it}$$

$$E[a_i + v_{it} | Z_i] = 0$$

Where Z_{it} as a vector of all strictly exogenous variables (including the instrument) and $\bar{Z}_i$ the mean of all time variant exogenous variables. In order to estimate the coefficients in equation [3] for the quantity of feed concentrate used by farmers, we use IV-CRE approach that uses a pooled 2SLS that includes the means of all time-varying controls to obtain standard errors that are robust to arbitrary serial correlation.

For our other technology adoption variables that are binary variables (e.g. use of herbicides, fertilizer and artificial insemination) we adopt the same basic unobserved panel data model in equation 2 with two important differences. First, in these models, y_{it1} is a binary variable that indicates 1 if the farmer adopted the technology and 0 otherwise for each time period and all the other control variables are identical to those in equation 2. Second, because our outcome variable y_{it1} and potentially endogenous market channel choice (m_{it}) are both binary variables, we cannot use the CRE-IV as described in the previous section. Following Papke and Wooldridge (2008) and Wooldridge (2003) we use a biprobit model (we will call it biprobit CRE) to estimate y_{it1} and a reduced form of m_{it} simultaneously. The biprobit CRE is similar to the CRE-IV only

adjusted to estimate the probability of farmer i choosing to use a technology adoption (given the binary nature of our technology variable equal to 1 if farmer adopted and 0 otherwise) and expressed below in the general form in equation 6:

$$\Pr (y_{it} = 1 | \mathbf{L}_{it}, \mathbf{LV}_i, \mathbf{X}_{it}) = \Phi(m_{it}\varphi + \mathbf{L}_{it}\beta_L + \mathbf{LV}_i\beta_{LV} + \mathbf{X}_{it}\beta_x + \gamma_t + c_i + v_{it}) \quad t=1,2 \quad [6]$$

Where we assume the distribution of Φ to be the cumulative distribution function of the standard normal distribution. In order to estimate this equation, we must also select a vector of instruments that satisfies the exclusion condition. In this case we select both the number processing plants and processors within the RUT and the department level. We assume that c_i can be modeled in the following way:

$$c_i = \psi + \bar{Z}_i\zeta_1 + \bar{L}_i\zeta_L + \bar{X}_i\zeta_x + a_i \quad [7]$$

$$D[c_i | \bar{Z}_i] = D[c_i | Z_i]$$

Where Z_{it} is a vector of the number of processing plants and processors within the RUT and the department level and $\bar{Z}_i$ is their mean. By replacing c_i in equation 6, we can write out the equations that were estimated using biprobit:

$$\Pr (y_{it} = 1 | m_{it}, Z_i, v_{it}, a_i) = \Phi(m_{it}\varphi + \mathbf{L}_{it}\beta_{L1} + \mathbf{LV}_i\beta_{LV1} + \mathbf{X}_{it}\beta_{x1} + \bar{L}_i\zeta_{L1} + \bar{X}_i\zeta_{x1} + \bar{Z}_i\zeta_1 + \gamma_{t1} + v_{it} + a_i) \quad [8]$$

$$\Pr (m_{it} = 1 | m_{it}, Z_i, v_{it}, a_i) = \Phi(\mathbf{L}_{it}\beta_{L2} + \mathbf{LV}_i\beta_{LV2} + \mathbf{X}_{it}\beta_{x2} + \mathbf{Z}_{it}\beta_Z + \bar{Z}_i\zeta_2 + \bar{L}_i\zeta_{L2} + \bar{X}_i\zeta_{x2} + \gamma_{t2} + u_{it}) \quad [9]$$

$$u_{it} | Z_i, \mathbf{L}_{it}, \mathbf{LV}_i, + \mathbf{X}_{it} \sim \text{Normal}(0,1)$$

After estimating the coefficients, we estimate the average partial effects and use a panel bootstrap for valid inference. In the case of the interactions, we calculated the average partial

effects of RUT when there is no violence (zero) and for the interaction we used the average violence index.

In the next section we first present the results for the market channel choice decision and then we present the technology adoption results by technology type.

VIII. RESULTS

i. Market Channel Choice

Table 1.7 presents the results of the effect of RUT sizes, violence levels, meso-level variables, and farmer-level variables on market channel choice. Table 1.8 shows the results of the same model but with separate regressions for each size of RUT. As well we included tables 1.12 and 13 in the appendix, which are the same models but estimated using pooled OLS as a robustness check. The following points emerge:

First, RUT size is positively associated with selling to the modern market channel. The probability that a farmer sells to the modern market increases by 8 percentage points if a farmer is located in a medium RUT and by 5 percentage points if they are located in Large RUT. These results are similar in table 1.12. This is consistent with the idea that bigger cities can more readily offer the services and information needed by the farmer to enable them to successfully participate in this channel.

Second, a higher density of modern milk processors is positively associated with selling to the modern market channel. An additional processor in a farmer's region is associated with a 5-percentage point higher probability of selling to the modern market at the 10% significance level. This is not surprising as with more modern milk buyers in the area, farmers have can have a better chance of interacting with actors in this channel and potentially negotiating prices and benefits.

Though higher density of processors is positively associated with participating in the modern market at both the RUT and the department level, the magnitude of the effect (a 5-percentage point difference versus 2 percentage points) indicate that having more processors at a more local level (RUT) is more important than having processors in a general region (department).

Table 1.7: Probit random effects panel estimation: marketing channel determination (base category: traditional market channel)

	Selling to Modern Milk Channel Average Marginal effects
Territorial Variables	
Urban Size (base= small RUTs)	
Medium RUTs	0.08* (0.044)
Large RUTs	0.05* (0.043)
Distances	
Distance to anchor city (minutes)	0.00 (0.001)
Distance to nearest milk processor (min)	-0.00 (0.001)
Violence Index	0.05 (0.076)
Violence Index*RUT	
Medium RUTs*Violence	0.08* (0.043)
Large RUT*Violence	0.06 (0.052)
Average rainfall (mm/month)	-0.00** (0.000)
Number of processors and processing plants (at RUT)	0.05** (0.024)
Number of processors and processing plants (at Department level)	0.02* (0.015)
Household Characteristics	
Education (base=no education)	
Primary/Highschool education	-0.01 (0.042)
College/graduate education	0.15** (0.068)

Table 1.7 (cont'd)

	Selling to Modern Milk Channel Average Marginal effects
Age head of household	-0.00 (0.001)
Female (male=0)	0.01 (0.026)
Farm/ non-farm assets	
Size of herd	0.01*** (0.002)
Size of herd2	-0.00*** (0.001)
log of owned land	0.04 (0.040)
Asset Index	-0.01 (0.010)
Own transportation (no=0)	-0.01 (0.023)
Part of an association (no=0)	0.29*** (0.061)
Year (2013=0)	-0.20 (0.139)

Brackets represent standard errors

Table made from survey information

Comparing across RUTs (Table 1.8) we see that this impact of the number of processors at RUT and department level is only positive and significant in small and large RUTs compared to medium RUTs. We also see, that in these two territories, having a higher number of processors in the local area is more significant than having processors at the department level. For small and large RUTs, an additional processor at the RUT level increases the probability of selling to the modern channel by 26 and 11 percentage points respectively (both statistically significant at 1%) while the effect of the number of processors at department level is not statistically significant for small RUTs. For large RUTs the number of processors at both department and RUT level are statistically significantly correlated with the likelihood of selling to the modern channel. In addition, the magnitude of the effect is still higher at RUT level (11 percentage points) compared

to the department level (3 percentage points). When looking at table 1.12 and 1.13 as a robustness check, we can see the same relationship, where a higher number of processors at the RUT levels and departmental levels are significant, especially for small and larger RUTs. Together these results clearly indicate that the benefits of agglomeration are more significant at a local level, and at times do not have an effect at a larger level.

Table 1.8: Probit random effects panel estimation: marketing channel determination (base category: traditional market channel) by RUT

	Selling to modern (Small RUTs)	Selling to modern (Medium RUTs)	Selling to modern (Large RUTs)
	Avg Marginal effects	Avg Marginal effects	Avg Marginal effects
Territorial Variables			
Distances (minutes)			
Distance to anchor city	-0.00 (0.001)	0.00 (0.002)	0.00 (0.001)
Distance to nearest milk processor	0.00 (0.001)	-0.00 (0.002)	-0.00 (0.001)
Violence Index	-0.73*** (0.273)	-0.47* (0.281)	0.28 (0.322)
Average rainfall (mm/month)	0.00*** (0.000)	-0.05*** (0.005)	-0.00 (0.000)
Number of processors and processing plants (at RUT)	0.26*** (0.088)	-0.06 (0.079)	0.11** (0.048)
Number of processors and processing plants (at Department level)	0.22 (0.361)	-0.34 (0.249)	0.03** (0.010)
Household Characteristics			
Education (base=no education)			
Primary/Highschool education	-0.09 (0.113)	0.04 (0.059)	0.13** (0.052)
College/graduate education	-0.08 (0.147)	0.25* (0.142)	0.31*** (0.096)

Table 1.8 (cont'd)

	Selling to modern (Small RUTs)	Selling to modern (Medium RUTs)	Selling to modern (Large RUTs)
	Avg Marginal effects	Avg Marginal effects	Avg Marginal effects
Age head of household	0.00 (0.001)	-0.00 (0.006)	-0.00** (0.002)
Female (male=0)	-0.00 (0.053)	-0.00 (0.047)	0.02 (0.047)
Farm/ Non-farm assets			
Size of herd	0.01*** (0.002)	-0.02 (0.027)	0.01*** (0.002)
Size of herd2	-0.00** (0.000)	-0.00 (0.000)	-0.00** (0.000)
log of owned land	0.01 (0.071)	0.05 (0.291)	0.09 (0.061)
Asset Index	0.00 (0.016)	0.00 (0.015)	0.01 (0.017)
Own transportation (no=0)	-0.01 (0.040)	-0.02 (0.032)	0.01 (0.049)
Part of an association (no=0)	0.28** (0.138)	0.30*** (0.075)	0.20* (0.103)
Year (2013=0)	-1.00*** (0.003)	0.50*** (0.149)	-0.51*** (0.070)

* Significant at P=0.10; ** significant at P=0.05; *** significant at P=0.01

Brackets represent standard errors

Table made from survey information

Third, we find that while violence generally doesn't have a statistically significant effect on selling to the modern market, but the interaction between RUT size and the level of violence appears to be important though only statistically significant at 10% (Table 1.7). We can see that compared to smaller RUTs, larger levels of violence have a positive impact on choosing a modern market channel in medium and large RUTs. Disaggregating the impact by RUT size (Table 1.8) this relationship becomes even more clear; in small RUTs violence has a strong negative impact on selling to the modern channel (significant at 1%) and in medium RUTs the effect is negative but

smaller (significant at 10%). In large RUTs, we see a statistically significant positive effect of violence. This might reflect that in relatively larger urban centers with high violence, the modern channels might actually increase farmers' confidence in marketing their product, making the modern channel more attractive. This relationship is also maintained through the pooled OLS results in table 1.13

Fourth, we find that on average and holding all else constant, more educated farmers (particularly having a college level education) is associated with a higher probability of selling to the modern market channel. This is consistent with the importance of knowledge and skills for being able to meet the requirements of selling to the modern market as well as having the negotiation skills to benefit from engaging with the channel. We also find a positive association between farmer herd size and selling to the modern market channel. However, the effects are quite small. Increasing the herd size by one cattle is associated with a 1 percentage point higher probability of selling to the modern channel at the 1% level. These findings might reflect anecdotal evidence that many large farmers also sell to small restaurants and bakeries in a traditional manner. This is because larger farmers do not need to consolidate their milk with other farmers and can sell it directly to artisanal and bigger processors. On the other hand, small farmers likely need to consolidate through traditional cooperatives and traders in order to be able to sell the milk, which are all part of the traditional milk market. This is consistent with table 1.2 which showed that in the regions with smaller herd sizes, cooperation with other farmers is more important.

Fifth, we find evidence of the importance of social capital for selling to the modern market channel. being part of an association is associated with a 29-percentage point higher probability

of selling to the modern market channel (Table 1.7). This impact is high across all RUTs (Table 1.8) but particularly small and medium RUTs where being in an association (holding all else constant) is associated with a 28 and 30 percentage point higher probability of selling to the modern market in small and medium RUTs compared to 20 percentage points in Large RUTs. The pooled OLS results in tables 1.13 and 1.14 present the same outcome. These results are consistent with the literature that notes the supporting role of associations in farmer commercialization, particularly for smaller farmers. There is a high share of milk producer associations that either process the milk themselves or help small farmers combine milk and then sell it to the modern market. These types of associations also aid in testing the milk and assess farmers in better practices, and are considered to be an essential part of the modern market channel.

ii. Market Channel Choice and RUT on use of feed

Table 1.9 presents the results from the IV CRE model on the impact of market channel choice on feed use for all farmers. Table 1.10 presents the same results but for each RUT independently. We also include tables 1.14 and 1.15 in the appendix, which show the results of the estimation of market channel choice using pooled OLS. Six key points emerge:

First, participating within the modern market channel overall has a positive effect of use of feed, but it is only significant in medium and small RUTs. Participating within the modern market is associated with an increase in the use of feed of 2.09 kg/feed/day at the 10% confidence level. This is consistent with the idea that selling to the modern market creates incentive for technology adoption. Nonetheless, when looking across RUTs (Table 1.10), we find that market channel choice is particularly important for feed use in small and medium RUTs compared to large RUTs. This likely reflect the fact in more urbanized areas, farmers are able to

access more information on the benefits of feed use and use such irrespective of their market choice. In more rural zones, the modern market serves as a disseminator of information.

Second, we find that relatively larger RUTs and density of input stores are associated with an increase in the use of feed, particularly medium size RUTs (Table 1.9). Being within a medium RUT is associated with a 0.5 kg higher amount of feed per cow per day (all else equal) compared to a small RUT. The importance of RUT size and density of stores likely reflects the important role of agglomeration of services (information and availability of the product). Surprisingly, the size of the effect of one extra agro-industrial input store at the department level is notably small. This low effect can potentially be explained by the fact that we are measuring the number of stores at the department level and not at the RUT level. As with number of modern processors in market channel choice, the agglomeration effect can diminish at the department level. It is important to note that these results were also consistent with the coefficient values estimates using pooled OLS (table 1.14).

Third, higher levels of violence (all things being equal) is not associated with a statistically significant effect on feed used. However, when violence is interacted with size, we see that violence is negatively associated with feed concentrate use in larger RUTs, though this is only statistically significant at 10%. Comparison across RUTs reveals that for medium and large RUTs, violence has a negative and significant effect on the quantity of feed used, all else equal (Table 1.10).

Table 1.9: IV correlated random effects: effect of market channel choice and RUT on feed use

<i>Feed Use (Kg/cow/day)</i>	<i>Coefficients</i>
Market Channel Choice	2.09* (4.622)
Territorial Variables	
Urban Size (base= small RUTs)	
Medium RUTs	0.50** (0.247)
Large RUTs	0.29 (0.268)
Distances	
Distance to anchor city (minutes)	0.00 (0.004)
Violence Index	-0.11 (0.219)
Violence Index*RUT	
Medium RUTs*Violence	-0.36 (0.302)
Large RUT*Violence	0.76* (0.446)
Price (at municipal level)	-0.00 (0.000)
Average rainfall (mm/month)	-0.00* (0.003)
Number of agro-industrial stores (at department level)	0.01** (0.002)
Household Characteristics	
Education (base=no education)	
Primary/Highschool education	0.16 (0.130)
College/graduate education	0.97* (0.558)
Age head of household	-0.01 (0.004)

Table 1.9 (cont'd)

<i>Feed Use (Kg/cow/day)</i>	Coefficients
Female (male=0)	0.15 (0.109)
Farm/ Non-farm assets	
Size of herd	0.01** (0.005)
Size of herd2	-0.00** (0.000)
log of owned land	-0.14* (0.179)
Asset Index	0.00 (0.036)
Own transportation (no=0)	0.03 (0.093)
Part of an association (no=0)	0.35 (0.689)
Year (2013=0)	0.20 (0.158)
Constant	0.10 (0.483)

Brackets represent standard errors

Table made from survey information

* Significant at P=0.10; ** significant at P=0.05;

*** significant at P=0.01

This is consistent with the literature, where farmers reduce their investments as they face potential displacement or have to deal with reduction in the number of buyers. As well, farmers can be more distrustful of input sellers in larger urban settings where farmers are not necessarily familiarized with them.

Fourth, higher percentage of land owned is associated with a lower quantity of feed used. Though one would expect farmers would invest more when they own the land, in this case farmers that do not own their own land might be reticent to invest in other practices, such as

pasture management, and would opt to adopt to a technology that is not directly tied to land use. In table 1.10 we see that this relationship is particularly significant in medium territories, as an increase in the share of land owned leads to a fall of 0.6 percentual points in the kg of feed used.

Fifth, herd size does not seem to play a big role in the use of feed. This result can show one of two things; first that small farmers are actually using feed as a way to increase production (and not more cattle) or that there is indirect effect from the low participation within the modern market that then leads to a fall in feed use. We argue that it is the first case, as from the data we have seen that on average 55% of small and micro farmers use feed, where only 26% of large farmers use feed. These results are also consistent with the estimation using pooled OLS in table 1.15.

Sixth, being part of an association has an insignificant effect on the quantity of feed used. This is surprising as one would expect associations to educate farmers on the benefits of feed. We believe that this low significance, further strengthens the argument that the modern market channel might be a source of dissemination when it comes to the benefits of feed use.

iii. Market Channel Choice and RUT on adoption of artificial insemination, use of cooling tanks and fertilizer and herbicide

Table 1.11 shows the results for the estimation of the adoption of artificial insemination, use of cooling tanks and adoption of fertilizer and herbicide from the biprobit CRE model (we also include in table 1.16 pooled OLS results). Six key points stand out:

Table 1.10: IV correlated random effects: effect of market channel choice on feed use by RUT

	Small RUT	Medium RUT	Large RUT
<i>Feed Use</i>	Coefficients	Coefficients	Coefficients
Market Channel Choice	2.51* (1.126)	0.82* (1.20)	2.23 (4.413)
Territorial Variables			
Distances			
Distance to anchor city (minutes)	0.03 (0.085)	0.01 (0.007)	0.01 (0.007)
Distance to agro-input stores (minutes)	-0.03 (0.067)	-0.00 (0.007)	-0.01 (0.006)
Violence Index	-1.95 (2.021)	-0.09* (0.284)	-0.90* (1.248)
Price (at municipal level)	-0.00 (0.003)	-0.00 (0.004)	-0.00 (0.001)
Average rainfall (mm/month)	-0.02* (0.063)	-0.10 (0.199)	-0.00 (0.003)
Number of agro-industrial stores (at department level)	0.01* (0.033)	-0.01 (0.029)	-0.00 (0.005)
Household Characteristics			
Education (base=no education)			
Primary/Highschool education	1.31 (3.292)	0.12 (0.210)	0.24 (0.430)
College/graduate education	0.74 (2.649)	0.71 (0.672)	0.13 (1.421)
Age head of household	-0.01 (0.031)	-0.01 (0.004)	0.00 (0.016)
Female (male=0)	0.10 (0.681)	0.28* (0.145)	-0.16 (0.246)
Farm/ Non-farm assets			
Size of herd	0.00 (0.004)	0.08** (0.038)	0.00*** (0.027)

Table 1.10 (cont'd)

<i>Feed Use</i>	Small RUT Coefficients	Medium RUT Coefficients	Large RUT Coefficients
Size of herd2	-0.00** (0.000)	0.00*** (0.000)	-0.00 (0.000)
log of owned land	-0.07 (1.101)	-0.60* (0.244)	-0.13 (0.272)
Asset Index	0.01 (0.301)	0.04 (0.073)	0.03 (0.084)
Own transportation (no=0)	0.21 (0.913)	-0.01 (0.105)	0.05 (0.186)
Part of an association (no=0)	-3.53 (10.074)	0.07 (0.919)	-0.78 (1.192)
Year (2013=0)	0.03 (1.460)	0.20 (0.158)	0.20 (0.158)
Constant	0.10 (0.483)	0.93 (2.009)	0.36 (0.487)

Brackets represent standard
errors

Table made from survey information

* Significant at P=0.10; ** significant at P=0.05; *** significant at P=0.01

First, participating within the modern channel is positively associated with the use of cooling tanks and herbicides and fertilizer. Selling to the modern market is associated with a 22-percentage point higher probability of using cooling tanks and 8 percentage point higher probability of using fertilizer and herbicide. These results are statistically significant at 1* and 10% respectively. The large coefficient on the adoption of cooling tanks is consistent with the expectation that modern market channel might encourage adoption of technologies with a short-term impact on quality. The absence of an effect of modern market channel choice on the

adoption of artificial insemination is also consistent with the idea that slower yielding technologies are less attractive as the modern market benefits can be delayed.

Table 1.11: Biprobit CRE: effect of market channel choice adoption of artificial insemination, use of cooling tank and fertilizer and herbicide

<i>Technology Adopted</i>	Artificial Insemination	Cooling Tanks	Fertilizer and herbicide
	AME	AME	AME
Market Channel Choice (base=traditional)	0.05 (0.108)	0.22*** (0.050)	0.08* (0.067)
Territorial Variables			
Urban Size (base= small RUTs)			
Medium RUTs	0.14*** (0.035)	0.05 (0.033)	0.00 (0.016)
Large RUTs	-0.07* (0.036)	0.01 (0.040)	0.06* (0.033)
Distances			
Distance to anchor city (minutes)	-0.01* (0.001)	-0.00 (0.000)	0.00** (0.000)
Violence Index	0.03 (0.035)	0.07 (0.041)	-0.07** (0.032)
Average rainfall (mm/month)	0.00*** (0.001)	-0.10 (0.199)	0.00 (0.000)
Number of agro-industrial stores (at department level)	0.01 (0.033)	-0.01 (0.029)	0.00* (0.000)
Violence Index*RUT			
Medium RUTs*Violence	0.16*** (0.033)	0.04 (0.029)	0.02 (0.023)
Large RUT*Violence	-0.08* (0.043)	0.01 (0.061)	0.09*** (0.026)

Table 1.11 (cont'd)

<i>Technology Adopted</i>	Artificial Insemination	Cooling Tanks	Fertilizer and herbicide
	AME	AME	AME
Household Characteristics			
Education (base=no education)			
Primary/Highschool education	0.08*** (0.026)	0.02 (0.020)	-0.01 (0.025)
College/graduate education	0.19*** (0.064)	0.03 (0.025)	0.022* (0.013)
Age head of household	0.00 (0.001)	0.00 (0.000)	-0.00** (0.000)
Female (male=0)	0.00 (0.022)	0.01 (0.014)	-0.02 (0.013)
Farm/ Non-farm assets			
Size of herd	0.00 (0.001)	0.08** (0.038)	0.00*** (0.001)
Size of herd2	-0.00 (0.001)	0.00*** (0.000)	-0.00** (0.000)
log of owned land	-0.02 (0.026)	0.01 (0.022)	0.01 (0.020)
Asset Index	-0.00 (0.002)	0.01* (0.007)	0.01* (0.005)
Own transportation (no=0)	-0.00 (0.005)	0.04** (0.018)	-0.02* (0.010)
Part of an association (no=0)	0.03* (0.017)	-0.06** (0.024)	-0.01 (0.022)
Year (2013=0)	0.00 (0.045)	-0.05 (0.031)	-0.03 (0.022)

Brackets represent standard errors

Table made from survey information

* Significant at P=0.10; ** significant at P=0.05; *** significant at P=0.01

APE= Average Marginal Effects

Second, the impact of RUT sizes on the probability of technology adoption varies with technology. While being in a medium size RUT is positively associated with adoption artificial insemination, the probability of using artificial insemination is lower for farmers located in large

RUTs. As noted earlier, artificial insemination requires more sensitive handling, which can easily be affected by higher levels of congestion present in larger urban settings. However, for the use of fertilizer and herbicide, being in a large RUT is positively associated with the probability of use. This might reflect that fertilizer and herbicides are more easily transported and handled, meaning that they are less prone to be affected by any congestion.

Third, the impact of violence level on technology adoption also varies with technology type and by RUT size. Higher levels of violence on average (all else held constant) are associated with a 7-percentage point lower probability of using fertilizer and herbicides. This is not surprising if expected displacements and uncertainty around this discourage investments in more medium-term technologies such as pasture development. In addition, while violence on its own is not statistically significantly associated with the use of artificial insemination (all else equal), we find that higher levels of urbanization (medium RUTs), violence is positively associated with the probability of using artificial insemination while it is negatively associated with use for large RUTs. This can be explained by the fact that when these technologies are more readily available (as they are in relatively bigger urban settings), they then can become a way to minimize risk in violent settings. However, as the urban setting gets bigger, congestion associated with violence becomes a deterrent to investing in long term technologies such as artificial insemination.

Fourth, the impact of association membership also varies with technology. While being a member of an association is positively associated with the adoption of artificial insemination, it is negatively associated with adoption of cooling tanks. The positive effect on AI adoption not surprising as associations can serve as institutions that spread information. With regards to

cooling tanks, the negative association might reflect the lower need for using a cooling tank since associations often receive milk from different farmers and sell it collectively.

Fifth, having a college/graduate education is associated with a higher probability of adopting AI and fertilizer and herbicide. This is not surprising having an education can reduce the learning curve when adopting a technology.

Six: the adoption of cooling tanks and fertilizer and herbicides are typically positively associated with farmers assets: the size of its herd, their index asset, if they have their own transportation. This is not surprising since these investments (e.g. cooling tanks are costly and fertilizer and herbicides often require upfront payments or access to credit), we would expect farmers with higher capital are able to invest in them compared to smaller farmers who may not have enough milk a day to justify renting or buying a cooling tank, nor the cash or access to credit to purchase inputs such as fertilizer and herbicides.

iv. Sequential adoption of market channel and technology adoption

This study assumes that the choice of market channel comes before feed use decisions. To confirm the reasonableness of this assumption, we constructed figures 1.2 through 1.5 that depicts the quantity of feed, and insemination, cooling tanks and fertilizer and herbicide use before modern market choice ($t=0$) and the quantity of feed farmers used after choosing the modern market.

This figure was constructed using the information of farmers that changed from the traditional channel to the modern channel between two possible time periods 2008 and 2013, and 2013 and 2018. The ts in these figures do not correspond to a specific year, they represent the time period (of the available data) before the change was made. For example, if a farmer

changed between 2008-2013, we recorded their technology use in 2008 under $t=-2$ and their technology use in 2013 in $t=+1$ and their 2018 technology use in $t=+2$. Now if a farmer changed between 2013-2018, we would record their 2008 technology use as $t=-2$, their 2013 technology use in $t=-1$ and their 2018 technology use in $t=+1$.

From figure 1.2, we can see that the median (middle line) and the maximum value of feed use (the second line), increase after the adoption of the modern market channel. In figures 1.3-1.5 we can see a similar trend, where the share of farmers that are using each of the technologies increases after choosing to sell to the modern channel. Though this is a descriptive analysis, it does somewhat hint to that modern market choice is happening before or sequentially with adoption of feed, artificial insemination, cooling tanks and fertilizer and herbicide.

Figure 1.2: Box plot of quantity of feed in the periods before and after choosing to sell to the modern channel

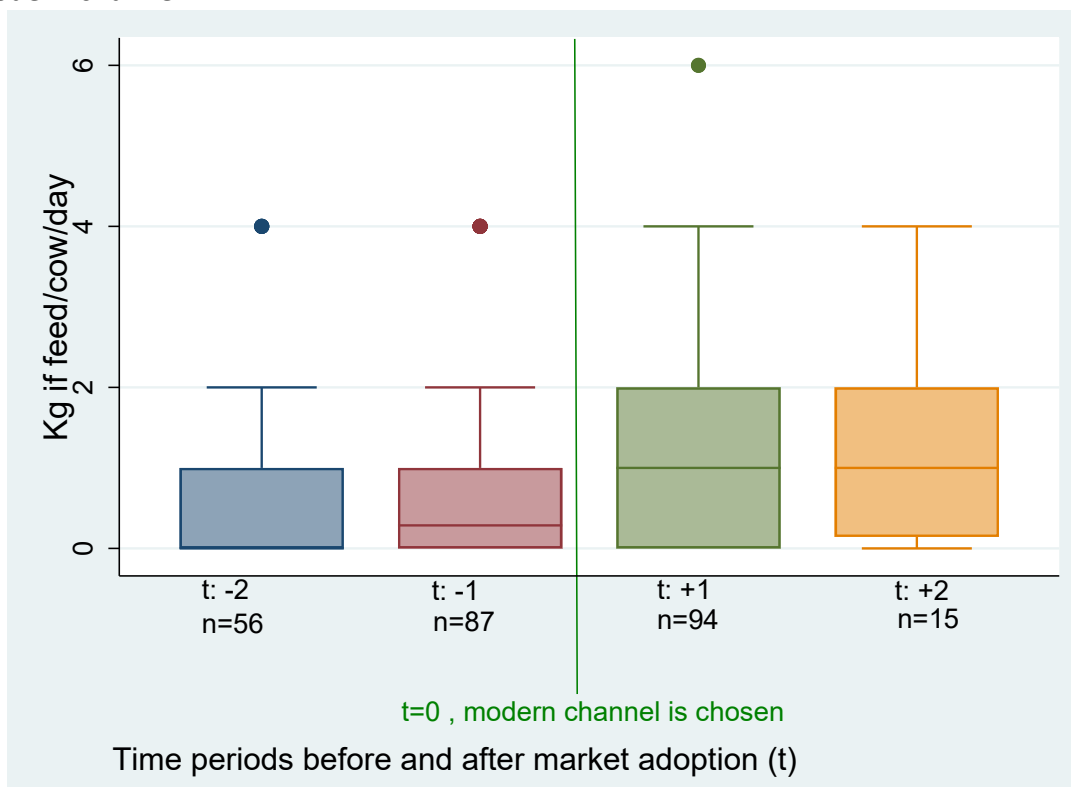
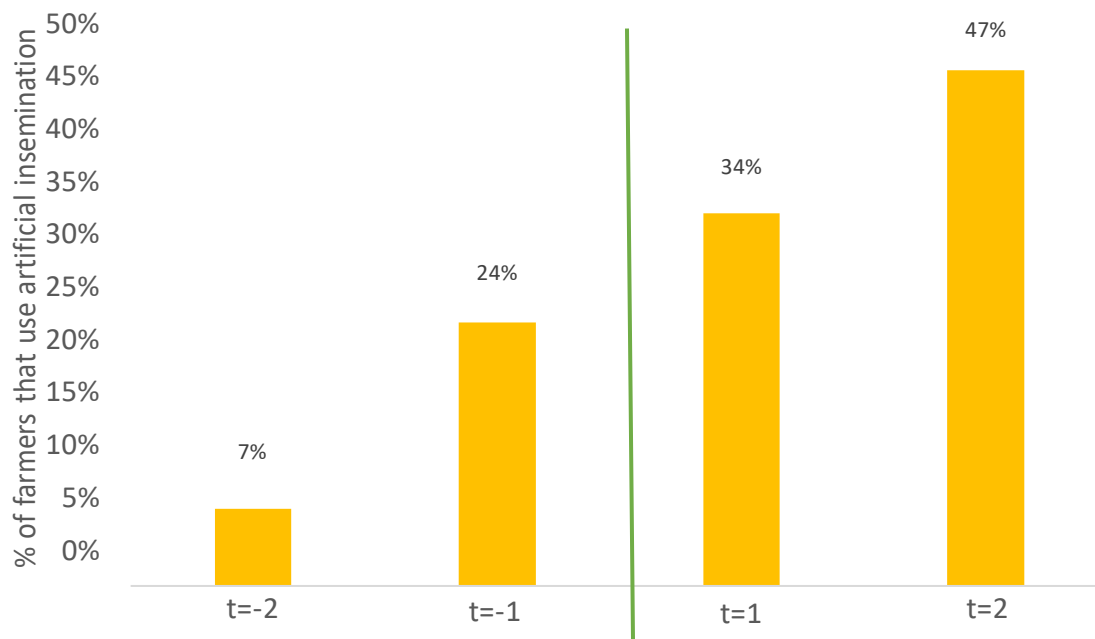


Figure 1.3: Bar graph of share of farmers that use artificial insemination in the periods before and after choosing to sell to the modern channel



t=0, Modern channel is chosen

Time periods before and after adotion

Figure 1.4: Bar graph of share of farmers that use cooling tanks in the periods before and after choosing to sell to the modern channel

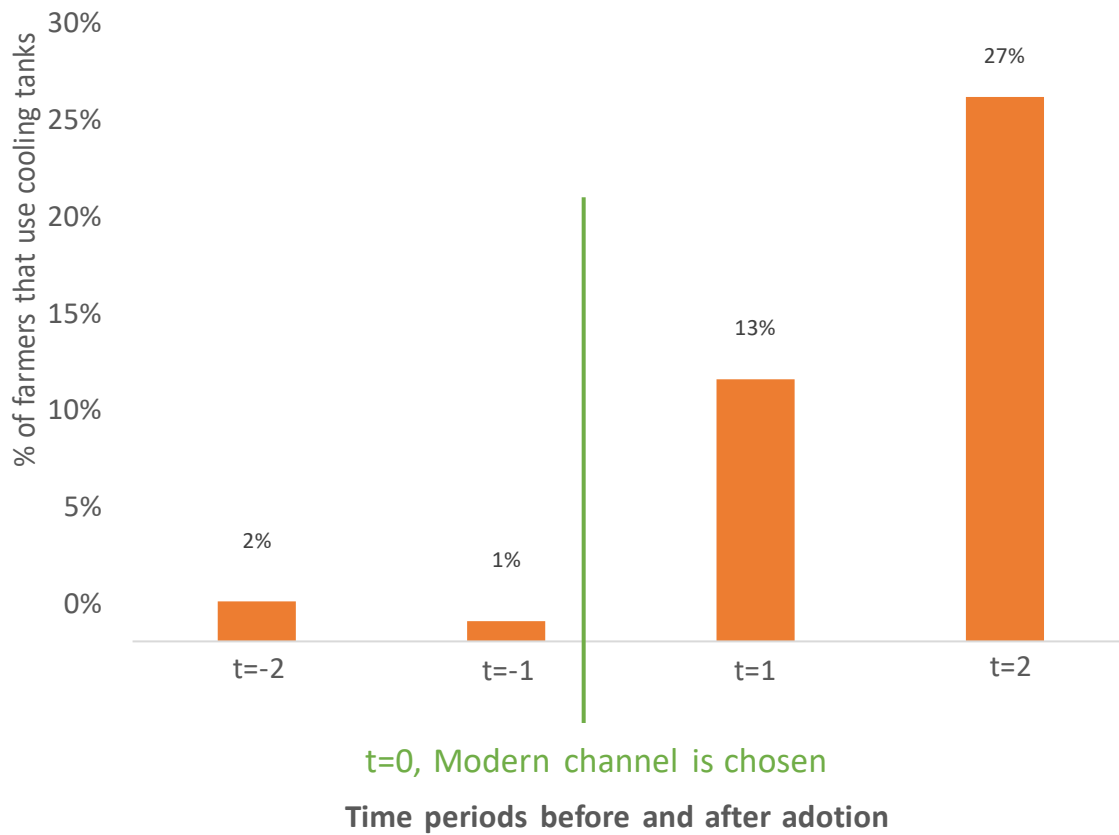
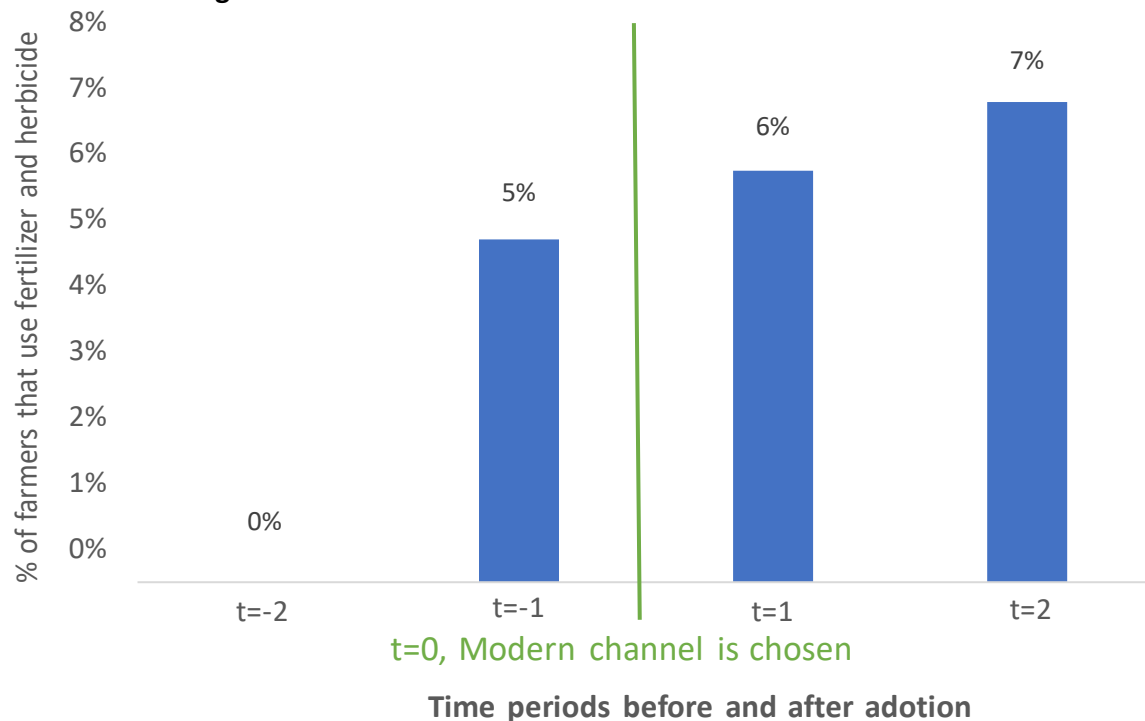


Figure 1.5: Bar graph of share of farmers that use fertilizer and herbicide in the periods before and after choosing to sell to the modern channel



IX. CONCLUSIONS

In this paper, we study the procurement systems of the modern market milk channel in Colombia and compare it with the traditional market channel. We investigate how the probability of supplying to a specific market channel has implications on use of concentrate, insemination, cooling tanks and the fertilizer and herbicide at the farm level while including important urbanization and territorial characteristics.

Overall, we have found that violence levels and urbanization levels have a joint effect on both the probability of selling to the modern market channel as well as the quantity of feed that is used, insemination and fertilizer and herbicide use. Still the sign of the effect varies across technologies. We find that in general violence has a negative effect on technology adoption, but when interacting it to urbanization levels, violence can serve as a risk mitigating tool.

As well we have seen that right hand determinants of market channel choice and technology adoption across different sized RUT. This is crucial, as in recent years, agricultural policy in Colombia has tended to be one-size-fit-all, where milk farmers are considered to be exactly the same (i.e., the determination of milk price is the same for all of the country). This can be inappropriate, as it is clear that farmers in less urbanized territories have different adoption strategies.

When exploring the impact of marketing channel on technology use, we find that farmers supplying the modern channels have a higher probability of using feed, and adopting cooling tanks and fertilizer and herbicide. Nevertheless, when comparing adoption rates across the two different marketing channels, it is important to emphasize that the share of adaptors and the quantity used within dairy enterprises are still very low. Given our results it is clear that urban channels may play a crucial role in offering the required incentives and support that can increase technology use,

Finally, we show that though larger farmers sell to the modern market channel, small farmers are not excluded. Moreover, we have found that size is not significant in explaining technology use with the exception of cooling tanks. This only strengthens the sub-strand of literature that argues that with adequate cost reducing investments, small farmers can participate within modern markets.

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APPENDIX

Table 1.12: Pooled OLS estimation: marketing channel determination

	Selling to Modern Milk Channel Average Marginal effects
Territorial Variables	
Urban Size (base= small RUTs)	
Medium RUTs	0.26* (0.153)
Large RUTs	0.18 (0.185)
Distances	
Distance to anchor city (minutes)	0.00 (0.002)
Distance to nearest milk processor (min)	-0.00 (0.002)
Violence Index	-0.25 (0.176)
Violence Index*RUT	
Medium RUTs*Violence	0.01 (0.257)
Large RUT*Violence	1.30** (0.519)
Average rainfall (mm/month)	-0.00 (0.001)
Number of processors and processing plants (at RUT)	0.57*** (0.091)
Number of processors and processing plants (at Department level)	0.24*** (0.059)
Household Characteristics	
Education (base=no education)	-0.04 (0.174)
Primary/Highschool education	0.50** (0.233)
College/graduate education	-0.04 (0.003)
Age head of household	-0.00 (0.003)
Female (male=0)	0.02 (0.107)

Table 1.12 (cont'd)

	Selling to Modern Milk Channel
	Average Marginal effects
Farm/ Non-farm assets	
Size of herd	0.03*** (0.006)
Size of herd2	-0.00*** (0.000)
log of owned land	0.15 (0.170)
Asset Index	0.05 (0.032)
Own transportation (no=0)	0.19** (0.086)
Part of an association (no=0)	0.54*** (0.094)
Year (2013=0)	-0.20 (0.139)
Constant	-1.73*** (0.346)

Brackets represent standard errors
Table made from survey information

Table 1.13: Pooled OLS: marketing channel determination by RUT

	Selling to modern (Small RUTs)	Selling to modern (Medium RUTs)	Selling to modern (Large RUTs)
Territorial Variables			
Distances (minutes)			
Distance to anchor city	-0.01 (0.006)	0.01 (0.006)	0.00 (0.005)
Distance to nearest milk processor	0.01 (0.006)	-0.01 (0.006)	-0.01 (0.005)
Violence Index	-1.30** (0.618)	-0.57* (0.318)	0.28 (0.322)
Average rainfall (mm/month)	0.01 (0.004)	-0.07*** (0.019)	-0.00 (0.002)
Number of processors and processing plants (at RUT)	1.48*** (0.439)	-1.26 (1.061)	1.33* (0.680)
Number of processors and processing plants (at Department level)	0.66 (1.502)	-2.85*** (0.663)	0.92*** (0.253)
Household Characteristics			
Education (base=no education)			
Primary/Highschool education	-0.25 (0.269)	0.20 (0.270)	0.75* (0.443)
College/graduate education	-0.16 (0.451)	0.95** (0.460)	1.40*** (0.504)
Age head of household	0.01 (0.007)	-0.00 (0.006)	-0.01** (0.007)
Female (male=0)	0.01 (0.205)	-0.05 (0.186)	0.11 (0.190)
Farm/ Non-farm assets			
Size of herd	0.02** (0.009)	0.04*** (0.014)	0.03*** (0.010)
Size of herd2	-0.00** (0.000)	-0.00 (0.000)	-0.00** (0.000)
log of owned land	-0.07 (0.340)	0.06 (0.294)	0.38 (0.256)
Asset Index	-0.11* (0.059)	0.16*** (0.060)	0.13** (0.051)

Table 1.13 (cont'd)

	Selling to modern (Small RUTs)	Selling to modern (Medium RUTs)	Selling to modern (Large RUTs)
Own transportation (no=0)	0.29* (0.152)	0.02 (0.147)	0.16 (0.159)
Part of an association (no=0)	0.16 (0.173)	0.80*** (0.150)	0.55*** (0.189)
Year (2013=0)	-5.20*** (1.561)	11.73*** (3.105)	-3.16*** (0.819)
Constant	-2.84*** (0.936)	3.26** (1.488)	-2.37*** (0.677)

* Significant at P=0.10; ** significant at P=0.05;

*** significant at P=0.01

Brackets represent standard errors

Table made from survey information

Table 1.14: Pooled OLS: effect of market channel choice and RUT on feed use

<i>Feed Use (Kg/cow/day)</i>	<i>Coefficients</i>
Market Channel Choice	0.10 (0.079)
Territorial Variables	
Urban Size (base= small RUTs)	
Medium RUTs	0.30*** (0.111)
Large RUTs	0.05 (0.143)
Distances	
Distance to anchor city (minutes)	0.00 (0.004)
Violence Index	-0.30*** (0.081)
Violence Index*RUT	
Medium RUTs*Violence	0.05 (0.169)
Large RUT*Violence	0.62** (0.314)
Price (at municipal level)	-0.00 (0.000)
Average rainfall (mm/month)	-0.00* (0.001)
Number of agro-industrial stores (at department level)	0.01** (0.001)
Household Characteristics	
Education (base=no education)	
Primary/Highschool education	0.14 (0.086)
College/graduate education	0.51*** (0.191)
Age head of household	-0.00* (0.002)

Table 1.14 (cont'd)

<i>Feed Use (Kg/cow/day)</i>	Coefficients
Female (male=0)	0.11 (0.071)
Farm/ Non-farm assets	
Size of herd	0.01** (0.003)
Size of herd2	-0.00** (0.000)
log of owned land	-0.18 (0.132)
Asset Index	0.08*** (0.022)
Own transportation (no=0)	0.02 (0.058)
Part of an association (no=0)	0.08 (0.077)
Year (2013=0)	-0.23** (0.091)
Constant	0.49 (0.317)

Brackets represent standard errors

Table made from survey information

* Significant at P=0.10; ** significant at P=0.05; *** significant at P=0.01

Table 1.15: Pooled OLS: effect of market channel choice on feed use by RUT

	Small RUT	Medium RUT	Large RUT
<i>Feed Use</i>	Coefficients	Coefficients	Coefficients
Market Channel Choice	-0.06 (0.121)	0.12 (0.120)	0.02 (0.163)
Territorial Variables			
Distances			
Distance to anchor city (minutes)	0.01 (0.006)	0.00 (0.006)	0.00 (0.005)
Distance to agro-input stores (minutes)	-0.01 (0.006)	-0.00 (0.006)	-0.01 (0.005)
Violence Index	-0.26*** (0.084)	-0.30** (0.141)	0.13 (0.325)
Price (at municipal level)	-0.00 (0.003)	-0.00 (0.004)	-0.00 (0.001)
Average rainfall (mm/month)	-0.00 (0.002)	-0.03*** (0.005)	-0.00** (0.001)
Number of agro-industrial stores (at department level)	0.00* (0.001)	-0.00 (0.002)	-0.00 (0.001)
Household Characteristics			
Education (base=no education)			
Primary/Highschool education	0.27*** (0.098)	0.10 (0.172)	-0.00 (0.155)
College/graduate education	0.01 (0.126)	0.59 (0.408)	0.65* (0.346)
Age head of household	-0.00 (0.004)	-0.00 (0.003)	-0.00 (0.004)
Female (male=0)	-0.00 (0.116)	0.28** (0.131)	-0.02 (0.113)
Farm/ Non-farm assets			
Size of herd	0.01** (0.003)	0.00 (0.013)	0.01* (0.005)

Table 1.15 (cont'd)

<i>Feed Use</i>	Small RUT	Medium RUT	Large RUT
	Coefficients	Coefficients	Coefficients
Size of herd2	-0.00*** (0.000)	0.00*** (0.000)	-0.00** (0.000)
log of owned land	0.08 (0.221)	-0.56** (0.243)	-0.03 (0.203)
Asset Index	0.06 (0.040)	0.11** (0.045)	0.07* (0.035)
Own transportation (no=0)	0.00 (0.097)	0.07 (0.104)	-0.01 (0.112)
Part of an association (no=0)	-0.01 (0.101)	0.11 (0.124)	-0.11 (0.126)
Year (2013=0)	-0.17 (0.131)	0.07 (0.104)	0.10 (0.148)
Constant	0.35 (0.513)	3.56*** (0.785)	1.28** (0.580)

Brackets represent standard errors

Table made from survey information

* Significant at P=0.10; ** significant at P=0.05; *** significant at P=0.01

Table 1.16: Pooled OLS: effect of market channel choice adoption of artificial insemination, use of cooling tank and fertilizer and herbicide

<i>Technology Adopted</i>	Artificial Insemination	Cooling Tanks	Fertilizer and herbicide
Market Channel Choice (base=traditional)	0.10*** (0.027)	0.10*** (0.017)	0.05*** (0.018)
Territorial Variables			
Urban Size (base= small RUTs)			
Medium RUTs	0.11*** (0.030)	0.03** (0.012)	0.00 (0.016)
Large RUTs	-0.07** (0.028)	0.04** (0.019)	0.10*** (0.033)
Distances			
Distance to anchor city (minutes)	-0.01* (0.000)	-0.00 (0.000)	0.00* (0.000)
Violence Index	-0.04** (0.017)	-0.03*** (0.010)	-0.02 (0.013)
Average rainfall (mm/month)	0.00*** (0.000)	0.00* (0.000)	0.00 (0.000)
Number of agro-industrial stores (at department level)	0.00*** (0.000)	0.00*** (0.000)	0.00 (0.000)
Violence Index*RUT			
Medium RUTs*Violence	-0.21*** (0.051)	0.04* (0.021)	0.06*** (0.021)
Large RUT*Violence	0.05 (0.062)	0.10** (0.043)	0.15** (0.069)
Household Characteristics			
Education (base=no education)			
Primary/Highschool education	0.07** (0.027)	0.01 (0.011)	-0.02 (0.021)
College/graduate education	0.20*** (0.055)	-0.00 (0.026)	0.11** (0.050)

Table 1.16 (cont'd)

<i>Technology Adopted</i>	Artificial Insemination	Cooling Tanks	Fertilizer and herbicide
Age head of household	0.00 (0.001)	0.00 (0.000)	-0.00** (0.000)
Female (male=0)	-0.01 (0.024)	0.01 (0.011)	-0.02* (0.011)
Farm/ Non-farm assets			
Size of herd	0.00* (0.000)	0.00*** (0.000)	0.00*** (0.000)
Size of herd2	-0.00* (0.000)	-0.00*** (0.000)	-0.00*** (0.000)
log of owned land	-0.01 (0.034)	0.01 (0.010)	0.01 (0.020)
Asset Index	0.02** (0.007)	0.00 (0.004)	0.01*** (0.005)
Own transportation (no=0)	0.03 (0.019)	0.00 (0.009)	-0.02* (0.010)
Part of an association (no=0)	0.03 (0.027)	0.01 (0.012)	0.01 (0.015)
Year (2013=0)	-0.10*** (0.027)	-0.02 (0.014)	-0.05** (0.023)
Constant	-0.36*** (0.093)	-0.15*** (0.049)	-0.06 (0.089)

Brackets represent standard errors

Table made from survey information

* Significant at P=0.10; ** significant at P=0.05; *** significant at P=0.01

CHAPTER 2

VULNERABILITY OF NIGERIAN MAIZE TRADERS TO A CONFLUENCE OF CLIMATE, VIOLENCE, DISEASE, AND COST SHOCKS

I. ABSTRACT

Using primary survey data on 1100 Nigerian maize traders for 2021 this study employs probit models to estimate maize trader vulnerabilities to exogenous shocks and its relationship to trader characteristics (gender, size, and location). The purpose of this research is to investigate five exogenous shocks: climate, violence, price hikes, spoilage, and COVID-19 lockdown, and analyze their association with trader characteristics reflecting vulnerability. The findings reveal that traders are prone to experiencing multiple shocks simultaneously, intensifying their impacts, with price shocks often accompanied by violence, climate, and COVID shocks. The poorer Northern region is disproportionately affected by shocks, with North traders experiencing more price shocks, and South traders experiencing more violence shocks due to their long supply chains in and from the North. Women are more prone to experiencing violence shocks, while men are more susceptible to severe climate events

This paper is the first of its kind in understanding the nature of these shocks on traders and uneven and unequal distribution of negative impacts. It is also original in being on Africa and based on a large sample of maize traders from a primary survey.

II. INTRODUCTION

The concept of multiple, mutually reinforcing shocks to food systems and rural communities has been in the literature for decades. For example, Bohle et al. (1994) analyzed climate change and social vulnerability, and observed that climate, disease, and conflict shocks coincided and mutually reinforced. They decomposed vulnerability to these shocks as risk of exposure,

inadequacy of the capacity to cope with the shock, and risk of severe impacts of the shock. FAO (2004) made similar points, emphasizing the confluence of climate shocks, conflict, and disease (then, HIV/AIDS). Gregory et al. (2005), Pingali et al. (2005), and Béné (2020) noted that these three shocks mutually reinforce and shock the full gamut of food system actors from farmers to supply-chain actors like traders to consumers. The 2020 piece shifted the disease emphasis in the debate from HIV/AIDS to COVID-19, and the latter then figured in the “Three C’s” of COVID-19, Conflict, and Climate chains that was a focus of the UN Food System Summit of 2021 (von Braun et al., 2023). Moreover, various papers studied bilateral links within the triad, such as between COVID-19 and armed conflict (Ide, 2021) and climate shocks/change and conflict (FAO, 2004). There were also studies of country-specific food system disruptions by confluences of shocks, such as Lara- Arévalo et al. (2023) for Honduras which analyzed links among climate shocks such as hurricanes, violence, and disease. Disaggregate, empirical analyses of the vulnerability to and impacts of these shocks, from our review of the literature, have tended to be concentrated in two sets. On the one hand, there have been numerous studies of impacts of shocks on farm households and vulnerable consumer groups. These have included studies of impacts of shocks on vulnerable populations including women, poor households, racially/ethnically marginalized groups, and communities in climate shock areas (e.g., Lara-Arévalo et al., 2023 in Honduras). They have also included studies of impacts of shocks like COVID-19, violence, and climate shocks on farm households (respectively, e.g., Ceballos et al., 2021 in Guatemala; Adelaja and George, 2019, in Nigeria and Kafando and Sakurai, 2024, in Burkina Faso; and Kumar et al., 2021 in India). Some studies focused on and surveyed farm households but analyzed impacts of shocks on input and

output supply chain actors interfacing with the farm households (e.g., onion farmers in Ethiopia during the COVID-19 pandemic; Worku and Ülkü, 2022).

On the other hand, there have been studies on the impacts of these three sets of shocks, singly or in confluence, on agrifood supply chains, either as entire chains, or as sets of supply chain actors such as traders and processors. Our review of the literature showed that this second set has far fewer studies than the above set. There are two categories of these studies.

First, studies have examined shocks such as COVID-19 on the aggregate volumes and prices of the supply chain; an example of this is Tripathi et al. (2023) for vegetable wholesale markets in India and Ruan et al. (2021) for vegetable wholesale markets in China; of ethnic and political violence on grain prices in wholesale markets in Kenya (Gil-Alana and Singh, 2015); and climate shocks and wholesale markets prices in India (Letta et al., 2022).

Second, studies have examined shocks, especially individual shocks like COVID-19, on particular supply chain actors, such as traders. An example is Naziri et al. (2023) analyzing the impact of COVID-19 restrictions on traders and processors in potato and fish value chains in Kenya. They assumed one element of vulnerability, that all actors were affected by the shock, and measured another element, how much the shock hurt their incomes and whether and how they coped with the shock. Our review of the literature shows that there are relatively few studies on how shocks affect the trader segment per se, especially in Africa, and few that determine whether a particular type of trader is affected by a shock.

There are two important gaps in the literature which also serve as our research questions that we address as the contribution of the present paper. (1) There have been few studies, especially in Africa, on how the midstream segments (e.g., traders) have been affected by any of

the three shocks noted above, and in particular, how they have been affected by a confluence or mixture of these shocks; (2) There have been few studies on the determinants of vulnerability (whether and how severely they have been affected) over types of traders reflecting vulnerable versus less vulnerable groups (in particular, females versus males, and smaller versus larger enterprises). These gaps on the impacts of a confluence of shocks are a subset of the more general gap in the literature of a dearth of studies on the midstream actors in value chains in developing regions (Barrett et al., 2022).

To address these research questions, we use data from two years (2017 and 2021) of our own unique survey of around 1,100 maize traders in Nigeria. Along with behavior and assets questions, the survey asked traders whether they had experienced the following shocks and how severe the impact had been on their business and how they coped with them: (1) climate shocks (road washouts, and floods and droughts in the farm areas supplying them); (2) conflict (such as Boko Haram activity) and banditry; (3) COVID-19 restrictions; (4) maize price surges and maize spoilage (that may arise at least partially from climate factors like drought and heat and humidity); (5) energy cost surges.

The paper proceeds as follows. Section 2 discusses the survey sampling method and sample characteristics. Section 3 presents the conceptual framework. Section 4 presents the regression model and estimation method. Section 5 presents descriptive results. Section 6 presents regression results. Section 6 concludes with implications.

III. DATA

We used a cross-section data set of maize traders collected in 2021 and shock experience data from a first survey on nearly the same sample in 2017. The sample of 1,195 maize traders in North and South Nigeria was sampled in 2017 with the following procedure.

First, we chose the four leading maize producing states (Plateau (6%, Kaduna 16%, Kano, 3%, and Katsina, 9%) in the main maize producing region (the North), and one leading maize producing and consuming state in the South (Oyo, 3%) which also has some maize production. This allows a North-South comparison. The shares are of total maize production in Nigeria (USDA, 2024). The ratio of maize production tons in the North states to those in Oyo is similar to the ratio of our trader sample in the North states versus Oyo.

Second, we did a census of all the urban and regional maize wholesale markets in each sampled state in the North and in the Ibadan area in Oyo in the South. The urban markets mainly feed the cities they are in. The regional markets are conduits from rural areas to Northern city markets and to the rest of the country (including the South).

Third, in each sample state of the North, we chose all the urban maize markets and the top five regional markets. In the South (state of Oyo) we chose all the urban markets in the Ibadan area. In Oyo there were no regional markets as the maize produced in the South mainly supplies the South urban markets.

Fourth, in each of the sampled urban markets we did a census of maize traders. 903 wholesalers across 23 city markets were listed. However, only 822 wholesalers were interviewed due to non-response of 81.

Fifth, in the 61 regional markets in the four North states we censused 6,358 maize traders. As we sought a sample of 600 traders (as even 385 gave a confidence interval of 95%), we chose the top (in total volume terms) 5 regional markets in each of the four sampled North states. This gave 20 regional markets. We categorized the traders in those 20 markets into two groups, large and small, based on their reported monthly sales during the peak season. Traders with volumes less than or equal to 32 tons were classified as small. Those exceeding 32 tons were categorized as large. To ensure diversity in scale within the sample, we used random selection that took into account the proportion of small and large traders in each market. The resultant 2017 sample was 822 urban and 600 regional market traders, hence 1,422.

Of the 1,422, 1,195 were resampled in 2021 as we were unable to find 227 traders. We tested for attrition bias and found that for the impacts of shocks the bias was not significant. Of the 1,195, 84 had exited trading between 2017 and 2021, so 1,111 were surveyed in November 2021. Table 2.1 shows the characteristics of the 1,111 surveyed traders and the located 84 who exited since 2017. 88% were male and 93% were in based in the North.

Table 2.2 shows why the located 84 who exited stopped maize trading: half dropped just to do more profitable business; a third dropped because they could not secure funds to continue trading; a tenth dropped because of insecurity (Boko Haram, robbers, banditry); 5% dropped because of death or fire; but none dropped due to COVID (disease or lockdown). 40% left before 2020 and 60% in 2020 or 2021. Thus, the timing of most dropping was during COVID and a surge in insecurity. It could be that being unable to secure funds or wanting to shift to a more profitable business were linked to COVID and the insecurity rise.

Table 2.1: Maize Trader Sample Characteristics, 2021 Survey

	Number	Share
Total interviews	1195	100
Maize trader interviews	1111	93
Traders that stopped trading	84	7
Gender		
Male	977	88
Female	134	12
Region		
North	1,030	93
South	81	7

Source: Authors' calculations

Table 2.2: Reasons traders exited trading after the 2017 survey & before the 2021 survey

Reasons For Leaving	Share of traders
Moved on to a more profitable business	51
Inability to secure funds to continue trading	35
Due to insecurity from herder-farmers conflict	0
Due to insecurity due to Boko Haram	1
Insecurity on the roads from armed robbers	1
Insecurity due to banditry and kidnapping	8
Personal shock such as death or fire	4
Due to contracting COVID	0
Due to movement restrictions during COVID lockdowns	0
Number of traders that stopped trading maize	84

Source: Authors' calculations

Our survey interviews were conducted by an enumerator and the trader, in person. The survey questionnaire covered trader's assets, procurement, value addition (such as drying maize), marketing, and shocks experienced and strategies to address the impacts of the shocks in 2021. The data in 2017 were in the same categories but we had not asked about

shocks/strategies in 2017. To control for climate, and exposure to violence, we use two sources of data. The first were data about the presence of non-state armed actors. These were calculated using Nigeria data from the Armed Conflict Location and Event Data Project (www.acleddata.com) which covers actors, locations, fatalities, and types of all reported political violence (e.g., abduction, attacks, explosions), sexual violence, looting, and property destruction. The second were temperature and rainfall data from the Climate Hazards Group InfraRed Precipitation with Station data collected by the US government (CHIRPS).

IV. CONCEPTUAL FRAMEWORK

Vulnerability has two dimensions: exposure and sensitivity. In the regressions (following Guido et al., 2020) we model vulnerability with two dependent variables: (1) exposure - the probability of experiencing an exogenous shock independent of its severity; and (2) impact - the probability of experiencing a shock that had a “large negative effect.”

We posit that the determinants of both exposure and impact are characteristics of the traders that feature how mobile they are and how exposed they are by the probable length of transit and location of their trading activities (measured by trading distance and urban location) and their general vulnerability (firm size in volume terms and gender).

We study five shocks: climate, violence, spoilage, increase in input prices, and a general exogenous shock. In the case of COVID 19, we only focus on the second measure (negative effect) as all traders were affected, but only some had severe outcomes. Each of these shocks was constructed as a summation over subsets of that general shock, as in Table 2.3. Each trader was asked if they had experienced any of the shocks in the right column in the past year (2020-2021).

If they answered yes to any of the questions, we could record the trader as having experienced that general shock.

Our hypotheses concerning the relationship between trader characteristics and shocks vary with the type of shock and its severity. We posit that larger traders would be more exposed to violence than smaller traders because larger traders might be perceived by bandits as wealthier and therefore a better target. We hypothesize that larger traders would suffer more spoilage because of the large volume of maize they move and the greater difficulty of monitoring its conditions. We posit smaller traders would be more affected by higher input prices as they may have less bargaining power to negotiate lower prices with suppliers.

The relationship between climate shocks and trader size is more ambiguous. A smaller trader may move grain a shorter distance and be more vulnerable to local weather and have less diversity of sourcing areas to manage risk. But larger traders often have more complex and interconnected supply chains, and source from longer routes which can be more vulnerable to disruptions caused by climate events such as droughts, floods, and storms.

The relationship between shocks and gender is also ambiguous. With regards to spoilage, COVID- 19, and price shocks, there is no inherent reason to believe that women traders are more vulnerable. These shocks affect individuals and businesses regardless of gender. However, research suggests that women, in general, may be disproportionately affected by climate shocks due to preexisting gender inequalities where they have less access to mitigating tools such as credit and education.

By contrast, it seems likely that female traders will be more vulnerable to violence than male traders. Terrorist groups sometimes use sexual violence to gain control through fear,

displace civilians, enforce unit cohesion among fighters, and even generate economic gains through trafficking (Bigio & Vogelstein, 2019).

Table 2.3: Classification of general types of shocks

Type of shock	Shocks traders responded to in survey
Climate	- Delay in receiving maize due to road wash-out - Maize production shortage due to floods - Logistics shortage or fee hike due to washouts or floods along roads from farm areas to wholesale markets - Maize production shortage due to droughts - Washout or flood in market destination area
Violence	- Boko Haram conflict constraining selling maize - Boko Haram conflict constraining buying maize from farmers - Boko Haram conflict in the North hurting buying from other traders - Farmer-herder conflict constraining buying maize from farmers - Other insecurity problems (including banditry/kidnappers) affecting the overall ability to trade maize
Spoilage	- Aflatoxin outbreak - Pests affecting stored maize - Rodents affecting stored maize - Serious spoilage of maize (e.g., due to mold)
Increase in input prices	- Significant increase in maize price - Significant increase in transport cost due to fuel price increases - Significant increase in fuel price
COVID19 (severe)	- Reduction of number of permanent or seasonal employees - Reduction of salary of your staff - Used own savings to support business - Sold own assets to support business

The location of victims, whether in the North or South, has the potential to affect the probability of experiencing a shock. We expect the North to have more extreme climate events as it is more arid (Nnaji et al., 2022). The North is also poorer in general so perhaps more vulnerable to input price hikes, controlling for trader scale. Finally, we hypothesize that some

shocks tend to occur together which can cause a trader more harm. Some shocks are linked, such as extreme climate events and spoilage.

We created 4 variables that measure the number of shocks that each trader has had by type of shock (climate, violence, spoilage, and higher input prices). These shocks per category correspond to the right-hand side variables in Table 2.3. If the trader responded yes to any of those shocks they were added within the total category. Some of the combinations are a priori more probable, such as climate shocks and spoilage. Some may not be necessarily probable, such as violence and climate shocks, as violent groups may be in unfavorable climate-shocked areas, but also might be in areas with better natural resources and more profits from holdups. We are not assuming causality among shocks but are simply studying their relationship and complementarity.

Within the control variables, we need to account for two sources of non-randomness. First, exposure to different shocks is not random in each territory. For example, violent groups establish themselves in regions with particular geographical and institutional characteristics that favor their overall objectives. Moreover, there are correlations between a region and particular shocks. For example, northern Nigeria has had more desertification, increasing the probability of climate and spoilage shocks. To account for this, we include climate variables (temperature and rainfall) and violence variables (number of years of the presence of an armed group) in each county. Note that “county” is used here for what in Nigeria is called an LGA or “local government area.” These variables indicate places that have poorer resources due to harsher weather conditions and more violent conflicts.

A second source of non-randomness comes from traders being able to adjust their behavior to reduce their exposure and sensitivity to shocks. Traders can choose where they sell their goods (North or South). It is likely that traders who are fairly certain about their exposure in a territory will take measures to prevent these shocks. Given that we are not able to measure the knowledge and awareness of a trader, we do have a useful proxy: if the trader experienced each shock (except COVID) in 2017. Due to this non-randomness we cannot claim causality but only correlations or associations.

We also include a set of trader characteristics that could affect the experience of a shock, including trading experience, schooling, rurality of traders (urban vs rural markets), association participation, own production of maize, and religion.

V. REGRESSION MODEL AND ESTIMATION METHOD

To understand the vulnerability of a trader to an exogenous shock, we use the following probit specification:

$$g_i = \mathbf{M}_i\beta_M + \mathbf{MV}_i\beta_{MV} + \mathbf{X}_i\beta_x + u_i \quad [1]$$

Where g_i is a binary indicator of shock for trader i , where $g_i = 1$ if the trader has experienced that shock and 0 otherwise in the past year. In this case we are going to estimate first 4 general shocks (disregarding severity): (1) Climate; (2) Violence; (3) Spoilage; and (4) Higher input prices. Then we are going to estimate 4 shocks which affect severity: (1) Climate (2) Violence (3) Higher input prices and (4) COVID19. It is important to note that we did not include spoilage within the second set of equations as only 12 traders suffered severe spoilage loss, and the lack of variability made the equation impossible to estimate.

M_i is a vector of our variables of interest including size, gender, location (North or South) of the main market where the trader sells as well as the number of climate, violence, spoilage, and input price shocks experienced by each trader and if they had experienced a COVID shock. It is important to note that we did not include the number of shocks for a specific category when we were estimating the probability of experiencing a shock in the same category. For example, when estimating a violence shock, we did not include the number of violence shocks.

MV_i is a vector of LGA-level variables that include the number of years of non-state armed actors' presence at the traders' location, and geographical variables such as average daily rainfall and temperature for 2021. X_{it} is a vector of control variables, including trader characteristics comprising education, trader experience, religion, trader production of maize, and trader participation in an association and location (urban vs rural market). As well we include dummy variables that show if the traders had experienced a violence, price, or general shock in 2017. $\beta_m, \beta_{MV}, \beta_x$ are the coefficient estimates associated with the study covariates. u_{it} is the error term which we assume is distributed $u_i | M_{it}, MV_i, X_i \sim N(0,1)$.

We model the probability of experiencing a shock by using the standard Probit framework:

$$\Pr(g_{it} = 1 | M_{it}, MV_i, X_{it}) = \Phi(M_{it}\beta_m + MV_i\beta_{MV} + X_{it}\beta_x) \quad t = 1 \dots T \quad [2]$$

Where Φ is the cumulative distribution function of the standard normal distribution. Following Wooldridge (2005) we use a conditional maximum likelihood estimator (MLE) to obtain the estimates of β_m, β_{MV} , and β_x . As well we calculate the average partial effect by averaging across the distribution of all observable covariates.

Given the inherently probabilistic nature of the study outcomes (facing different kinds of shocks), we have used the probit model to accommodate the non-linear relationship between our explanatory variables (predictors) and the probability of facing these shocks (measured as 1 if the shock is faced and 0, otherwise). This stands in contrast to the linear probability model (LPM) which presupposes a linear relationship and hence imposes a constant partial effect of our explanatory variables on the probability of experiencing a particular shock. In addition, the probit model also avoids any predicted probabilities of experiencing a shock being less than zero or greater than 1. We are also able to estimate the average partial effects of each explanatory variable (quantify the average change in the probability of the event for a one-unit change in each explanatory variable) which facilitates meaningful comparisons between different predictors of traders' probability of facing different shocks.²

To check the goodness of fit of our model we calculate the Pseudo R-square (McFadden R Squared) recommended as a measure of Goodness of fit (Greene, 2006) for discrete models. This approach involves assessing the log-likelihood value of each of our models in comparison to a restricted model. In the restricted model, non-intercept coefficients are constrained to zero, with the stipulation that all coefficients in the regression model must differ from zero. Overall, a poorly functioning model (independent variables have no/low explanatory power) will have a pseudo-R squared close to zero. It is important to note that a pseudo-R square is not the same as an R square used in LPM and will have lower values. This implies that even pseudo-R squared values of 0.2 are considered a good fit (McFadden, 1974).

² We have selected the probit model over the logit model only due to a slight preference for the normality assumption for the error term. However, we confirm that the results from the probit and logit models are statistically and economically similar.

VI. DESCRIPTIVE STATISTICS

In the following we discuss the key findings shown in the descriptive Tables 2.4-2.11. Each Table shows the shares of traders having experienced a particular type of shock and the severity of these.

i. Climate/weather shocks

Table 2.4 shows that 14% of traders experienced a climate/weather shock. Table 2.5 shows that larger traders were more apt (at 15%) than smaller traders (at 11%) to experience this shock (with a highly significant statistical difference). Male and female operators do not differ in experience of climate shocks (Table 2.6). These results suggest that traders who depend on a larger catchment area for their procurement are more vulnerable to droughts in the sending zones and floods along the roads including in their own areas.

Table 2.4 breaks down the types of climate shocks into droughts, floods, and road washouts. Floods were experienced by 4% of the traders, only 3% of those based in the North but 18% based in the wetter South. Droughts affected only 2% of the traders; interestingly, that share was 1% in the North and 6% in the South. One reason may be that the South traders source heavily from areas in the North that were drought-affected. The most common shock was road washout (possibly because of a lack of road culverts to divert flood flows); 11% of the North traders and 26% of the South traders experienced washouts. This could be due to regional climate differences but our survey did not enumerate where the roads washed out. Given that the North depends on their own region (where most maize is produced) and the South traders mainly source from the North, the climate shocks in the North appear to transmit to the South.

Table 2.4 also shows the severity of each climate shock. Of the traders that experienced a climate shock, 6% of traders suffered no effect, 37% had only a small negative effect, and 57% were severely hurt. The table also shows that 33% of the traders completely recovered from the climate shock. The largest negative effect came from road washouts (59%) versus only about 40% for the droughts and floods. A third of the traders completely recovered from droughts and washouts but more (46%) recovered completely from floods.

Table 2.4: Climate shocks affecting maize traders August 2020 – July 2021

	Farm area flood	Farm area drought	Road wash out	Any Climate Shock
% traders affected by climate shock	4	2	12	14
<i>Conditional on having this shock:</i>				
% traders affected in the North	3	1	11	13
% traders affected in the South	18	6	26	26
Avg. years of trading experience	19	21	20	20
% traders had no effect	2	5	7	6
% traders had small negative effect	57	59	34	37
% traders had big negative effect	41	36	59	57
% Total effects	100	100	100	100
% traders completely recovered	33	46	33	33

Source: Authors' calculations

Table 2.5: Shocks by size and region of the maize trader

	Size (share)		T-test
	Small	Large	T statistic
Share of wholesalers	42	58	
<i>Shocks</i>			
Drought/Floods/Road Washout	11	15	-2.16***
Boko Haram conflict on maize selling/buying	15	16	-0.22
Farmer-herder conflict on maize buying	19	19	-0.00
Banditry on maize trading	36	44	-2.32**
Spoilage	1	3	-1.15
Jump in maize price	58	57	0.31
Jump in truck fuel price	33	42	-3.03***
Negative Covid Effects	61	66	-1.57
	Meta Region (share)		T-test
	North	South	T statistic
Share of Wholesalers	93	7	
<i>Shocks</i>			
Drought/Floods/Road Washout	13	26	-3.20***
Boko Haram conflict on maize selling/buying	13	40	-6.43***
Farmer-herder conflict on maize buying	18	43	-5.31***
Banditry on maize trading	41	48	-1.35
Spoilage	3	1	0.87
Jump in maize price	58	61	-0.58
Jump in truck fuel price	41	27	2.33**
Negative Covid Effects	64	61	0.6

* p<0.1; ** p<0.05; *** p<0.01

Regions: North includes: Katsina, Kano, Kaduna and Plateau. South includes Oyo state.

Size: large traders are those that sold 32 tons (or more) per month within the high season

Table 2.6: Shocks by gender of the maize trader

	Sex (share)		T-test
	Male	Female	T statistic
Share of Wholesalers	88	12	
<i>Shocks</i>			
Drought/Floods/ Road Wash	14	14	0.02
Boko Haram conflict on maize selling/buying	15	18	-1.08
Farmer-herder conflict on maize buying	17	44	-7.65***
Banditry on maize trading	40	54	-3.03***
Spoilage	3	3	-0.15
Jump in maize price	57	69	-2.63***
Jump in truck fuel price	42	26	3.46***
Negative Covid Effects	63	73	-2.27**

* p<0.1; ** p<0.05; *** p<0.01

ii. Conflict shocks

Table 2.7 shows that 48% of the traders experienced a conflict shock. The probability of the shock was 1.4 times higher for South- and North-based traders (Table 2.5). This may be due to South-based traders being much more exposed to conflicts due to their much longer transit distances than North-based traders. It also might be due to South traders' having to specialize in sourcing from certain zones in the North where conflict is higher while the North traders have perhaps more options.

Table 2.7 breaks down the types of conflict shocks into Boko Haram, farm-herder conflicts, and banditry. Boko Haram violence is experienced by 15% of the traders overall, with 13% among North-based traders and 40% for South-based (Table 2.5). Farmer-herder conflicts affect 20% of the traders overall, again with the imbalance of 18% of the North-based and 42%

of the South-based (Table 2.5). Banditry, however, is more equally shared, affecting 42% overall with 41% of North and 48% of South based traders. These findings are consistent with anecdotal evidence noting the rise of banditry across the country and the expansion of security concerns in Nigeria beyond Boko Haram to farmer-herder conflicts and banditry (George and Adelaja 2022). Again, as with North climate shocks, given the South importantly depends on the North the conflict shocks in the North transmit to the South.

Table 2.7: Conflict shocks affecting maize traders

	Boko Haram conflict on selling/buying	Farmer-herder conflict on buying from farmers	Banditry on maize trading	Any type of violence
% traders affected by this shock	15	20	42	48
<i>Conditional on having this shock:</i>				
% traders affected in the North	13	18	41	47
% traders affected in the South	40	42	48	66
% traders had no effect	3	7	5	5
% traders had small effect	31	60	41	39
% traders had big negative effect	66	33	54	56
% Total effects	100	100	100	100
% traders completely recovered	52	34	24	75

Source: Authors' calculations

Table 2.5 shows that the difference between North and South based traders in terms of conflict exposure is highly significant statistically for Boko Haram conflict and farmer-herder conflict but not for banditry. This suggests banditry is more widespread in both the North and South and the long transit between the two. Table 2.5 shows that larger traders were more apt

(at 44%) than smaller traders (at 36%) to experience banditry (but the difference was not significant for the other conflict shocks).

Table 2.6 shows that female traders were much more likely than males to experience farmer-herder conflict shocks (44 to 17%) and banditry (54 to 40%) with both differences highly significant. This is likely driven by the situation in Plateau State where most female maize traders are found and farmer-herder conflict is rampant.

Table 2.7 shows the perceived effects of the shocks for all conflict shocks taken together (the last column) controlling for their having experienced the shock: 5% of traders went without an effect, 39% had only a small negative effect, and 56% were severely hurt. Note the similarity of these effects with those of climate. The largest negative effect came from Boko Haram, followed by banditry and then by farmer-herder conflict.

However, 75% of the traders completely recovered from the violence shocks (for all shocks taken together). Complete recovery was 52% for Boko Haram shocks, 34% for herder-farm conflict, and 24% for banditry. Overall, our conflict shock results highlight the significant challenge from banditry and herder-farmer conflicts, exceeding those of Boko Haram. Yet banditry and herder-farmer conflicts are less discussed in international debates compared to Boko Haram.

iii. Spoilage/loss/waste shocks

Table 2.8 shows that only 3% reported experiencing a spoilage/loss/waste shock. We posit that spoilage/loss is so extremely low (compared to the traditional image one has of this in the international debates) because: (1) the traders tend to buy maize already in bags; (2) they move

the bags fast, just a few days of transit; (3) they seldom store the bags and if they store, they store for a short time only (Kwon et al. 2023).

The probability of the spoilage shock was 3 times higher for North-based traders than South-based (although without a statistically significant difference). This may be due to North-based traders sourcing from a wider variety of North sources with a greater variety of spoilage controls; the grain sold to the South traders may have been sorted/selected for long distance sale.

Table 2.8: Spoilage/loss/waste shocks affecting maize traders

	ALL: Aflatoxin, Insects, rodents and mold in maize	Aflatoxin	Insects	Rodents	Spoilage from mold
% traders affected by this shock	3	0.2	1.1	1.8	0.5
<i>Conditional on having this shock:</i>					
% traders affected in the North	3				
% traders affected in the South	1				
% traders had no effect	5				
% traders had small negative effect	56				
% traders had big negative effect	39				
% Total effects	100				
% traders completely recovered	44				

Source: Authors' calculations

Table 2.8 breaks down the spoilage shocks into aflatoxin, insects, rodents, and spoilage from mold. We do not show further information in rows in these columns because the shares are

so slight. Damage from rodents is the highest but is still only 1.8%, with insects at 1.1% of traders, mold, 0.5%, and aflatoxin only 0.2%.

Table 2.5 shows spoilage shock exposure is thrice higher for large traders but the difference is not significantly statistically. Table 2.6 shows there is no difference in spoilage shocks between male and female traders.

iv. Cost shocks

Table 2.9 shows that cost shocks are experienced by 63% of traders. We asked about the two most important inputs to traders (besides labor), the maize price and the truck fuel price. Maize price surges were felt by 58% and fuel price surges, 40%. The difference between other shocks and the fuel price shock is that presumably all traders face the same or similar fuel prices while maize prices can differ over zones, despite arbitrage.

The North and South traders are equally affected by maize price surges, presumably because these are mainly in the North where most maize is produced and both depend mainly on the North for maize. Interestingly, the share of traders being affected by fuel price surges is much more in the North (41%) than in the South (27%). This may be due to differences between the regions in fuel prices and/or fuel access. It may also be that South traders in depending on 3PLS for the long supply chains are working with larger trucks which may have greater access to limited fuel or at least get their fuel along major highways where the prices may be more competitive.

Table 2.5 shows fuel price shock exposure is 1.5 times more frequent for large traders (and the difference is statistically significant); this could be because larger traders tend to travel or source from longer distances. By contrast there is no significant difference in maize price

surges felt by large versus small traders; that might suggest a lack of “bargaining power” by larger traders relative to small traders.

Table 2.9: Cost shocks affecting maize traders

	Jump in maize price	Jump in truck fuel price	Any Jump in input price
% traders affected by this shock	58	40	63
<i>Conditional on having this shock:</i>			
% traders affected in the North	58	41	63
% traders affected in the South	61	27	62
% traders had no effect	5	7	7
% traders had small negative effect	42	39	39
% traders had big negative effect	53	54	54
% Total effects	100	100	100
% traders completely recovered	23	21	20

Source: Authors' calculations

Table 2.6 shows males are nearly twice as apt to experience a fuel price shock as females. This could be because females trade closer to their base and have smaller operations. Females also are somewhat more apt to experience a maize price surge than males (and that difference is significant statistically).

Table 2.9 shows the effects of the shocks for both price shocks taken together controlling for their having experienced the shock: 7% of traders went without an effect, 39% had only a small negative effect, and 54% were severely hurt. The shares did not differ much between the two types of price shocks. A very low share (compared with the other shocks) of traders fully recovered from the price shocks, just around 20% for both prices.

v. COVID related shocks (mainly from lockdowns)

Since all traders experienced a COVID-19 shock, we focus on those traders that were more severely affected. Particularly, we considered a severe shock if because of COVID- 19 they reported doing any of the following: reduced employees or staff salaries, or used own savings to weather shock, or sold own assets. Table 2.10 shows that 64% of the traders experienced a severe COVID-related shock. This was similar in the North (64% of traders) and the South (61%). There was no significant difference between small and large traders. But female traders were a little more likely to experience the shock (Table 2.5).

v. Confluence of shocks

Table 2.11 shows the distribution of shocks by traders, and by traders who experienced each type of shock. The data show that fully 66% of the traders experienced 1-4 shocks in the same year. Only 20% experienced more than that and 13% experienced fewer. The bottom rows (from Climate+ to COVID 19 +) show the share of traders who experienced both a specific shock (climate, violence, etc.) and other shocks. In most of the cases, traders that experienced a specific shock also experienced 2 or 3 other shocks. For example, 34% of the traders that experienced a violence shock experienced 2 non-violence related shocks.

Table 2.10: COVID-related shocks on maize traders

COVID-19 related shock, if: reduced the number of permanent or seasonal employees; reduced staff salary; used own savings to support business; sold own assets to support business	
% traders affected by this shock	64
% traders affected in the North	64
% traders affected in the South	61

Source: Authors' calculations

Table 2.11: Shares of traders undergoing no shock, one shock, or multiple shocks

	Number of shocks														
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	13+
% traders	13	16	16	15	19	8	6	2	1	1	0.7	0.6	0.4	0.5	100%
Climate +	1	6	15	17	21	11	6	6	11	6					100%
Violence +	12	16	34	12	17	5	2	1	1	0					100%
Spoilage +	6	6	19	13	16	16	10	6	3	3					100%
Price +	10	32	23	19	4	4	4	1	2	0.4	0.8				100%
COVID 19 +	12	19	17	26	11	8	3	2	1.3	0.8	0.1	0.6	0.7		100%

Source: Authors' calculations

VII. RESULTS

In Tables 2.12 and 2.13 we present the average marginal effects of the probit model for shock incidence and for severe shock incidence respectively. There are six main findings.

First, there is generally a confluence of shocks, particularly in relationship to price shocks. Table 2.12 shows price shocks are correlated with violence, climate and COVID shocks. An increase of one climate related shock is associated with an increase in the probability of experiencing a price shock by 74% (column (4) in Table 2.12). An additional violence shock is associated with an increase in the probability of experiencing a price shock of 36%. The interpretation is that climate and violence shocks can lead to road closures and maize yield drops which lead to increases in transportation costs and input costs. As well, extreme weather events and violent attacks can hinder overall market sizes and market prices. This is consistent with the literature as Bar-Nahum *et al.* (2020) and Van Den Hoek (2017) show that escalations of violence

are correlated with market prices and market activity decline. Letta *et al.*, (2022) also shows that extreme weather events (particularly drought) increase food prices.

Table 2.12: Probit regression results (Average partial effects): determinants of shock incidence by type of shock

VARIABLES	(1) Climate	(2) Violence	(3) Spoilage	(4) High prices
Number of climate shocks		0.08 (0.104)	0.46** (0.189)	0.74*** (0.208)
Number violence shocks	0.12* (0.064)		0.11 (0.105)	0.36*** (0.080)
Number of spoilage shocks	1.07*** (0.298)	-0.05 (0.328)		0.54 (0.468)
Number of price shocks	0.32*** (0.066)	0.16** (0.068)	-0.02 (0.123)	
Negative COVID effect (base = no negative effects)	-0.15 (0.180)	0.36*** (0.131)	0.17 (0.267)	0.89*** (0.136)
Gender (base male)	-0.38 (0.256)	0.33 (0.294)	0.29 (0.375)	0.34 (0.238)
Size (base small)	0.25 (0.180)	-0.10 (0.132)	-0.24 (0.289)	-0.05 (0.145)
Region (base North)	-0.37 (0.463)	1.06** (0.356)	-1.18 (1.065)	-0.89* (0.425)
General Shocks in 2017	0.09 (0.146)		0.39 (0.258)	
Violence Shock in 2017		0.13 (0.218)		
Price shock in 2017				-0.12 (0.129)
Location (base rural)	-0.26 (0.233)	0.68*** (0.171)	0.40 (0.267)	0.43** (0.207)
Years violence presence	-0.04 (0.041)	0.09*** (0.024)	0.03 (0.033)	0.03 (0.023)
Mean rainfall 2021	0.82** (0.325)	-0.46* (0.239)	-0.43 (0.366)	0.03 (0.239)
Mean temperature 2021	0.34*** (0.095)	-0.05 (0.076)	-0.09 (0.127)	0.15** (0.076)

Table 2.12 (cont'd)

VARIABLES	(1) Climate	(2) Violence	(3) Spoilage	(4) High prices
Age	0.00 (0.010)	-0.02** (0.008)	-0.04** (0.017)	-0.01 (0.009)
Experience	-0.00 (0.010)	0.02 (0.010)	0.03** (0.013)	0.01 (0.010)
Islamic (base: Christian)	-0.54 (0.358)	0.27 (0.237)	1.12** (0.475)	-0.78*** (0.245)
Produces own maize (base 0)	-0.09 (0.258)	1.27*** (0.177)	0.52 (0.349)	-0.36** (0.174)
Trader is part of an association (base 0)	0.40** (0.158)	0.06 (0.129)	0.55** (0.237)	0.11 (0.140)
Constant	-14.36*** (3.776)	2.14 (2.851)	0.91 (4.257)	-4.40 (2.809)
Observations	1,032	1,032	1,032	1,032
McFadden R2	0.21	0.176	0.261	0.213

Robust standard errors in parentheses

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

Price shocks can also exacerbate the effect of climate and violence shocks. Price shocks increase the probability of experiencing severe climate, violence, and COVID shocks. Price shocks have a far bigger incidence in predicting severe climate and violence shocks than general exposure to the climate or violence shock. The addition of one price shock increases the probability of experiencing a severe climate shock by 50% (Table 2.13 column 1), and a violence shock by 29% (Table 2.13 column 2). This can be interpreted as higher input and transportation costs constraining traders in their actions to mitigate risk.

Table 2.13: Probit regression results (Average partial effects): determinants of severe shock incidence by type of shock

VARIABLES	(1) Severe climate	(2) Severe violence	(3) Severe prices	(4) Negative COVID
Number of climate shocks		-0.13 (0.115)	0.41*** (0.122)	-0.24** (0.119)
Number violence shocks	0.10 (0.080)		0.21*** (0.057)	0.21*** (0.055)
Number of spoilage shocks	1.21*** (0.324)	0.28 (0.271)	0.38 (0.278)	-0.06 (0.275)
Number of price shocks	0.50*** (0.084)	0.29*** (0.059)		0.36*** (0.057)
Negative COVID effect (base no negative effects)	-0.31 (0.193)	0.19 (0.137)	0.36*** (0.132)	
Sex (base male)	-1.15** (0.557)	0.49* (0.269)	-0.02 (0.307)	-0.16 (0.265)
Size (base small)	0.08 (0.227)	-0.07 (0.146)	-0.48*** (0.146)	-0.20 (0.132)
Region (base North)	-0.57 (0.849)	-1.46*** (0.474)	-3.45*** (0.590)	-0.20 (0.434)
General Shocks in 2017	-0.01 (0.175)			
Violence Shock in 2017		0.41* (0.234)		
Price shock in 2017			-0.04 (0.130)	
Location (base rural)	0.16 (0.215)	0.84*** (0.169)	0.69*** (0.168)	-0.89*** (0.181)
Years violence presence	0.03 (0.042)	0.03 (0.023)	0.01 (0.021)	0.00 (0.026)
Mean rainfall 2021	-0.24 (0.369)	0.36 (0.262)	0.82*** (0.208)	0.38 (0.236)
Mean temperature 2021	0.18 (0.117)	0.18** (0.086)	0.39*** (0.078)	-0.01 (0.077)
Age	-0.01 (0.012)	-0.01 (0.008)	-0.01 (0.009)	-0.02*** (0.008)
Experience	-0.01 (0.014)	0.03*** (0.009)	0.00 (0.010)	0.01 (0.009)

Table 2.13 (cont'd)

VARIABLES	(1) Severe climate	(2) Severe violence	(3) Severe prices	(4) Negative COVID
Islamic (base: Christian)	-0.20 (0.354)	1.07*** (0.302)	-0.16 (0.298)	-0.19 (0.244)
Produces own maize (base 0)	-0.35 (0.357)	0.54*** (0.182)	-0.25 (0.190)	0.06 (0.180)
Is part of an association (base 0)	0.26 (0.183)	0.08 (0.140)	-0.04 (0.132)	0.34** (0.135)
Constant	-6.74 (4.534)	-8.87*** (3.266)	-14.53*** (2.802)	0.27 (2.913)
Observations	1,032	1,032	1,032	1,032
McFadden R2	0.307	0.247	0.217	0.154

Robust standard errors in parentheses

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

Moreover, climate and price shocks can spur looting and violent protests. This is consistent with the literature as Bellemare (2015) and Hendrix and Haggard (2015) establish connections between worldwide food prices and the incidence of food-related riots and urban unrest, measured by protests, demonstrations, and acts of violence.

Second, there is a positive relationship between COVID and violence shocks. Table 2.12 shows that traders who experienced a severe COVID shock were 36% more likely to experience a violence shock as well (column 2). This goes hand in hand with recent studies that have shown that COVID worsened governance standards, including leadership failures which have led to less democratic accountability, high levels of corruption and higher inequality rates (Kaufman, 2020). It might also have been because of terror organizations (such as Boko Haram in Nigeria) using the pandemic to gain influence and credibility, with their recruitment and radicalization strategies being amplified through acts of charity, offering financial resources, and other forms of related assistance (United Nations Security Council, 2021).

Third, though the exposure to shocks is often not statistically significant with respect to region (North versus South), when accounting for severity of shocks, the North is disproportionately affected. Table 2.12 shows “region” has no effect on the probability of experiencing a climate or spoilage shock, but South traders have a higher incidence of violence shocks and Northern traders have a higher incidence of price shocks.

However, Table 2.13 shows that South traders are less likely to experience severe shocks (when compared with the North traders), and this is particularly significant for severe violence and severe price shocks. This may be because Northern Nigeria has the greatest share of population in extreme poverty and a high violence and crime rate (Jaiyeola and Choga, 2021). Overall, higher poverty rates can leave individuals with fewer financial tools to mitigate risk and are therefore more exposed to severe shocks.

Fourth, in Tables 2.12 and 2.13, there are no significant differences across trader sizes, except on severity of price shocks. Smaller traders are 48% more likely (than larger traders) to be affected by severe price shocks (Table 2.13 column 3). Overall, small traders have less bargaining power and may not be able to negotiate lower prices with suppliers. As a result, they may have to pay more for the same inputs as larger competitors.

Fifth, the effects of gender across shocks are varied. There is no statistical significance with regards to general shock incidence, but when it comes to severe shocks, women have a higher chance of experiencing a violence shock and men of experiencing a severe climate event. This highlights the challenges faced by women during periods of turmoil. As well, this is consistent with the literature as in the realm of terrorist attacks, women often find themselves bearing a disproportionately heavy burden (Okoli & Azom, 2019). Notably, certain terrorist groups resort

to using sexual violence as a tool for asserting control by instilling fear, displacing civilians, fostering unity among their ranks, and, disturbingly, even deriving economic gains through trafficking (Bigio & Vogelstein, 2019). Men appear more exposed to the climate shocks.

Sixth, traders' farming maize is a strategy to mitigate maize price shocks but can expose (through rural area location specific activity, and usually in the North where most maize is grown) them to violence shocks. Table 2.12 shows that traders who grow maize had a 36% lower chance of experiencing maize price shocks (column 4) but a 127% higher chance of experiencing violence shocks (column 2). The latter is made more explicable by our knowing that non-state armed actors and farmer herder conflicts have led to the destruction of farm fields in the North in particular.

VIII. CONCLUSIONS

This paper has six key findings. First, maize traders in long supply chains in Nigeria were exposed to a confluence of shocks, especially price shocks, which are often accompanied by violence, climate, and COVID shocks. Second, COVID and violence shocks have a positive relationship, as traders who experienced a severe COVID shock were more likely to experience a violence shock. Third, the North region, poorer and with more rural violence than other regions, was disproportionately affected by shocks, with Northern traders having a higher incidence of price shocks, and Southern traders experiencing more violence shocks but linked to their involvement in long supply chains of maize mainly from the North. Fourth, except for severe price shocks, there were no significant differences across trader sizes in terms of shock incidence. Fifth, the effects of gender on shocks were varied, with women having a higher chance of experiencing a violence shock and men being more likely to experience a severe climate event. Finally, traders'

farming maize mitigates their exposure to price shocks but increases their vulnerability to violence shocks.

The study highlights the importance of understanding the confluence of shocks and their impacts on maize traders. The findings suggest that shocks such as COVID, violence, and climate can have severe consequences for traders, especially those living in or sourcing from northern Nigeria. On one hand, the identification of victims is crucial to developing effective strategies that can help support traders and strengthen security in food systems. On the other hand, it is important that government and donor programs support traders' ability to handle these shocks and/or reduce their exposure to them.

Maize related policies in Nigeria tend to focus on increased productivity (e.g. promoting expanded use of improved seeds and good agricultural practices) and maize trade restrictions (e.g., bans or quotas on maize importation and foreign exchange limitations for maize importation) (Nevin, 2021). However, our results indicate that more attention needs to be paid to improving the efficiency and general operations of the domestic supply chain for maize in Nigeria.

For example, strategies are needed to address conflict in major maize production areas as well as along trade routes often more than 1000 km between the major production areas in the north and major consumption areas in the south. These efforts will not only directly support increased maize production in the country but will bolster the impact of trader backward integration efforts to guarantee their supply of maize and minimize their exposure to high and fluctuating prices.

Better rural, urban and inter-state road infrastructure is also necessary. The highest negative impact from any shock was due to road washouts. Poor infrastructure is also an important determinant of maize prices. This indicates the need for adequate attention to further road construction (rural and urban) and maintenance across Nigeria. Improved drainage as well as regular maintenance and repair of roads and bridges can significantly reduce the prevalence of road washouts and associated transportation bottlenecks. Increased access to affordable alternative transportation options (such as rail) could also reduce trader exposure to poor and unsafe roads and potentially lower the cost for moving food items such as maize across the country.

Finally, our study findings suggest that in addition to improved infrastructure and better security, trader exposure to and/or the impact of external shocks could be mitigated by carefully designed finance and/or insurance programs that are simple enough for traders to understand and access, with affordable premiums (or interest rates) and implemented by trusted agents.

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CHAPTER 3

NAVIGATING CONFLICT: HOW VIOLENT EVENTS INFLUENCE MAIZE TRADERS' PRICES IN NIGERIA

I. ABSTRACT

This paper examines how violence has affected the maize procurement prices for Nigerian maize traders. Violence has become more common in Nigeria in the past 10-15 years. This includes attacks and kidnappings by Boko Haram (continuously in the world news) and more recently increased farmer-herder conflicts, kidnappings, and banditry. This increased violence hurts farming, rural labor supply, welfare, and food security (George et al. 2021, Arias et al, 2017, and Bozzoli & Brück, 2009). Past literature has studied micro-level effects of violence, but in the agrifood sector it has focused almost exclusively on farmers. The effects of violence on other food supply chain actors, including traders, has been relatively neglected.

For our paper, we analyzed survey data collected from 1100 maize farmers in 2022. Focusing on both violent events and the presence of non-state armed actors (NSAA), our study aims to understand how violent conflict influences the prices paid by maize traders. We explore variations across different seasons and types of maize to capture the multifaceted dynamics at play.

Our findings reveal significant and substantial effects of violence on maize procurement prices for Nigerian traders, with variations observed between when violence occurs at the traders' own Local Government Areas (LGAs) and when violence takes place at the LGAs of their suppliers. Armed confrontations and explosions push prices higher for both white and yellow maize by increasing transaction costs through disrupted production and market closures.

Conversely, violence against civilians lowers prices, likely due to reduced demand as safety concerns deter buyers, particularly in supplier LGAs.

Our analysis also highlights the significant joint effect of violence and urban density, emphasizing the pronounced impact of violence on prices in urbanized areas. Additionally, engaging in maize production and being part of an association are found to be significantly related to lower maize prices, suggesting mediation effects and/or advantageous bargaining positions for traders involved in agriculture and associations.

II. INTRODUCTION

Violent conflict is among the major global challenges and a key disrupter of agrifood value chains. Though the instances of traditional warfare have fallen, conflict and violence are on the rise, especially between non-state actors such as political militias and international terrorist groups (Nations, n.d.). Recent violent conflict has disrupted global value chains creating shortages of raw materials (especially grain and the inputs to grow it), logistical challenges on transportation, and an increase in prices. The Ukrainian war has increased the cost of shipping wheat to the Black Sea from US\$20-40 per ton to US\$120-150 per ton, and the current Hamas-Israel conflict, the participation of Iran increased oil prices by 9% (Teng, 2023). Still, there has been limited rigorous evidence of how violence affects activities of value chain actors, especially midstream actors along value chains (such as wholesalers) and the prices they pay for their products.

This gap in research is especially important in countries like Nigeria, where the number of armed confrontations, explosions and cases of violence against civilians have more than tripled in the last three years (Armed Conflict Location and Event Data Project-ACLED), but very little has been done to understand the impact of violence on citizens and agrifood firms. The research that

has been done thus far, has focused mostly on farmers and households, particularly with regards to labor supply and food insecurity (Adelaja & George, 2019; Dimelu et al., 2017; George et al., 2020, 2021; Nnaji et al., 2022).

Till date, we have not found any research that has focused on the impact of conflict on the activities of traders, or other midstream agrifood value chain actors. This gap exists despite the fact that these food supply chain actors are critical for distributing more than 85% of the food consumed in the country. Remarkably, approximately 90% of the nation's total food consumption is locally procured, with 95% sourced domestically, leaving a mere 5% attributed to imports. Notably, maize, a key staple and animal feed ingredient, traverses long-distance supply chains from the North to the South (Liverpool-Tasie et al., 2021). This means that increases in the price of maize procured by wholesalers, due to violence can have a substantial effect on the price and subsequent consumption of maize and other products made with maize (including cereals and animal source foods). In this article we focus on answering the general question: does violent conflict have an effect on the price paid by maize traders?

In this regard, two general literature strands are key: (1) the effect of violence on firms; and (2) the effect of violence on consumption through prices. Generally speaking, literature on the effect of violence on firms has mostly focused on the effects on production (particularly the contraction in production). For the longest time the economic consequences of violent conflict had been mostly investigated through a macroeconomic lens; where national data was used to understand the effect of conflict (particularly civil wars) on gross domestic product (Barro 1991, Collier 1991 and, Collier and Hoeffler 2008). This literature revealed the catastrophic effects of war on GDP growth, where it is estimated that during a civil war the annual growth rate is reduced

by 2.2% and 15-year civil war could reduce GDP/cap by 15% (Collier 1999). In addition, many studies on post-war reconstruction make the case that countries with especially destructive conflict, will generally lag in economic growth unless there is a significant institutional change (Collier & Duponchel, 2013; Collier & Hoeffler, 2004; Kang & Meernik, 2005).

More recently, there has been an increase in the literature that has focused on the microeconomic effects of violent conflict. This literature started with a focus on the cost and consequences of violent conflict on households and individuals (Kalyvas & Kocher, 2009; Verwimp et al., 2009; George et al., 2020) and has slowly started to estimate the consequences of violent conflict of firms by focusing on farmers (Brück et al., 2013). Through the use of household farm models and empirical data it has been shown that violent shocks often lead to a trade-off between maximizing welfare and maximizing physical security (Verwimp et al., 2019), leading to a fall in both consumption and production. In the case of firms, the thin body of evidence has linked violence and production, through its effects on productivity losses and the exit of firms (Camacho & Rodriguez, 2013; Collier & Duponchel, 2013; Klapper, Richmond and Tran, 2013; Utar, 2020). A few papers argue that the fall in productivity comes from the fact that many firms end up being survivalist rather than growth enhancing during a time of conflict. For example, farmers who are impacted by violent conflicts might transition from lucrative commercial farming to subsistence agriculture to meet their households' food needs, leading to adverse outcomes for farm productivity (Arias et al., 2017; Brück et al., 2013). Another sub-branch proposed that the contraction has more to do with a loss of human capital, be it from deaths, displacements or a fall in general skill levels (Collier & Duponchel, 2013). The majority of this literature is describing this contraction in production and very few consider price as both a

determinant and a consequence of the contraction itself. The lone study on this by Steinhübel & Minten (2023) tests the effect of violence exposure on different farm level production inputs and show that different levels of violence have an effect on input expenditure and the price of urea. Still, no studies (the authors have found) have considered the impact on midstream actors such as traders despite the fact that farm level-decisions affect price of supplies to other actors within the value chain such as processors and wholesalers and therefore needs to be considered.

On the consumption side, there is also a dearth in research linking violence to food prices. There are two small branches that consider this link; one that studies the effect of violence on food insecurity and one that studies its effect on access to markets. The literature that has explored the relationship between violence and price, tends to focus on how violence affects food consumption through prices. Both George et al. (2020) and D'Souza and Jolliffe (2013) estimate the relationship between violence and prices in order to understand the pathways through which the Boko Haram conflict impacts food security. Both find that the increase in prices leads to slightly smaller reductions in food security in areas with more conflict, theorizing that households in violent regions have learned to cope by smoothing their consumption. This in turn implies that price shocks effects on consumption due to violence are less severe in areas where conflict has been prolonged.

The second branch focuses more on the effect that violence has on access to actual food products through markets. In general, many violent actors target markets or the areas around markets making it harder for citizens to access them, be it because road access is affected, or shops within the market itself close down. Bar-Nahum et al. (2020) shows that escalations of violence on the city of Hebron (West Bank) reduced potential market size by 14.5% and a

simulation on extreme violence increased market prices by 1%. As well, Van Den Hoek (2017) finds that there is a negative correlation between Boko Haram attacks and market activity.

It is important to note that there is a branch of literature that has looked at the relationship between prices and violence, albeit not on food prices, and that is hedonic pricing. In general, hedonic pricing models have been used to identify price factors by posing that these depend on both the internal characteristics of the good but also external factors affecting it (Rosen, 1974). This literature has mostly been used to understand the meso-level characteristics that affect house prices. In the case of violent crime, various papers have shown that high violence and low perceived security negatively affects housing prices and valuations of other environment factors such as parks and schools (Delgado & Wences, 2020). Others have even linked the existence of food deserts to housing prices, and how the lack of markets generally decrease house prices (Caudill et al., 2021). Though not measured directly, these three branches of literature point to the fact that violence in general causes a reduction in demand.

Overall, there is evidence from microeconomic literature that violence is related to both a contraction in production and a fall in demand. Violent conflict leads both farmers and consumers to modify their consumption and production behaviors, especially if there is persistent violence in the region where households and producers live. What still remains missing is the implication of violence on midstream actors (such as wholesalers) activities; for example, the supply price for maize. If farmers are reducing their production due to violence, then higher prices are expected in high violence areas. Yet, if demand for maize is waning in areas that have high violence, farmers in those regions might have to decrease their prices in order to be able to sell their maize. Understanding this relationship is the first step to determining how violence

affects not only households in violent areas, but also all households in a region or country who depend on supply chains as a source of inputs, output market or even as an entrepreneurial activity associated with a lateral service for any segment of the maize value chain. As traders distribute grain, any price shocks they face for procuring maize will have an effect across the region or country.

This paper responds to this gap in the literature by focusing on the following two research questions. First, does high violence levels in the main base and main procurement location of traders increase the price of maize paid by traders? We focus on both the locations where a trader's base is (i.e. his main stall/firm activity is located) as well as the location of their main supplier since a traders' activities are not necessarily tied to one specific location and can be exposed to violence at both locations. Steinhübel & Minten (2023) in fact show that effect of conflict on agricultural development is location-dependent, therefore including all locations for traders is key.

Second, does the recent and continuous presence of non-state armed actors (NSAA) in these locations have an effect on the price paid by traders? In other contexts, households continually exposed to violence have learned to cope with price shocks from violence (George et al., 2020; D'Souza and Jolliffe, 2013). Is this the case for Nigerian maize traders? Is it possible that continued exposure to violence by traders and their main suppliers have reduced the effect that violence has on price, and that they are able to find mitigating strategies.

To address these two research questions, we leverage on primary data from a survey administered in 2021 to a sample of Nigerian maize traders. The survey collected detailed information about the trading practices, preferences, and challenges faced by these individuals.

We supplement the primary data on trader activities with the ACLED (Armed Conflict Location and Event Data Project) violence dataset to systematically identify and quantify the impact of violence on maize prices.

Given the significance of seasonality in shaping market dynamics, we deliberately consider procurement information for both the high and low trading seasons, and relate this to the violence levels of each season. Very few papers have included this aspect within the measurement of the effect of violence. This is important in Nigeria where Van Den Hoek (2017) observed that while Boko Haram has not explicitly articulated a strategy related to controlling or influencing agricultural production, their monthly activities seem to coincide with crucial periods in the agricultural calendar for northern Nigeria. By considering how violent events and other contextual factors influence maize prices during both high and low seasons, we aim to unravel the complex interplay between violence, agricultural markets, and the temporal variations inherent in maize trading.

We find a significant impact of violence on maize procurement prices for Nigerian traders, with distinct effects depending on the location of violence. Armed confrontations and explosions push prices higher for both white and yellow maize by increasing transaction costs through disrupted production and market closures. On the other hand, violence against civilians lowers prices, likely due to reduced demand as safety concerns deter buyers, particularly in supplier LGAs.

This paper also shows that prolonged exposure to violence and shocks from prior seasons impact prices differently by maize type. In areas with sustained exposure to violence, traders seem to adapt over time, developing strategies that help lower prices, especially for yellow

maize. However, even with adaptive mechanisms, some input costs for yellow maize remain elevated due to its role as animal feed and a less adaptable supply chain. Additionally, the study highlights a notable interaction effect between urban density and violence, with urbanized regions experiencing stronger price volatility, consistent with prior research on the vulnerabilities of densely populated areas during conflict.

Finally, we find that maize production and association membership emerge as effective ways for traders to mitigate violence-driven price volatility, as these provide them with bargaining power and resilience against shocks.

The article is organized as follows. First, then we present some background information on Nigeria, on maize production and violence using external sources. Then we describe the data structure, the conceptual framework and the empirical strategy. This is followed by a description of our study sample vis a vis the key outcome and explanatory variables and the results of our regression analysis (as well as some robustness checks). The final section presents our conclusions with their policy implications.

III. MAIZE TRADING AND VIOLENCE IN NIGERIA

i. Maize planting, harvesting and trade

Maize is an important staple food crop in Nigeria. Among cereals, it occupies the largest area under cultivation, and its photoperiod insensitivity allows for year-round growth. However, with less than 10% of maize production relying on irrigation (Wossen et al., 2023), Nigeria still operates with two main planting seasons, differing between northern and southern regions (Adeite, 2021). Typically, the wet season extends from May to July (starting earlier in the south and ending later), while the dry season occurs between October and March (Gona, 2023). Harvesting takes place

50 to 110 days after planting, depending on whether the crop is grown for cobs or grain (Kamara et al., n.d.). Though maize is produced all around the country, the majority is sourced from the north. The top 5 producing states are located there, and they produce 44% of all the maize in Nigeria (Nevin et al., 2021).

There are two dominant kinds of maize traded in Nigeria: white and yellow. These particular maize varieties are extensively consumed within Nigeria with white maize primarily catering to human consumption, while yellow maize is predominantly used for animal feed (Nevin et al., 2021).

The maize production pattern shapes trading practices, determining the timing and geographic focus of maize trade. The harvest schedule sets the high season for maize trading from August to February, marked by peak availability and increased market activity, while the low season spans March to July with reduced supply. The majority of traders source maize from the north to supply the entire country, with Liverpool-Tasie et al. (2021) noting that 80% of maize for southern traders is sourced from the north. On average, southern traders cover a distance of approximately 300 kilometers between buying and selling locations, reflecting the significant role of northern production in meeting demand across Nigeria.

Traders can source from many diverse suppliers, such as farmers, field brokers, other traders and from markets. Most of these transactions happen at the location of the supplier (in farms or markets). They then sell mostly to other traders, retailers, consumers and feed mills. (Liverpool-Tasie et al., 2021).

ii. Escalation of Violence

In recent years, violent conflict has been escalating at an alarming rate in Nigeria. According to the Armed Conflict Location and Event Data Project (ACLED), the number of recorded events of violence against civilians has increased almost 20-fold from 124 in 2009 to 2,254 in 2022. Moreover, the UN Office for the Coordination of Humanitarian Affairs claims that the deteriorating security situation in Nigeria has resulted in more than 8.4 million people requiring urgent assistance (Global Centre for the Responsibility to Protect, 2023).

This situation can mostly be attributed to the rise of Boko Haram activities, farmer-herder conflicts (FHC) and general banditry. Boko Haram is widely recognized as an Islamic terrorist organization that originated in Nigeria in 2002. The group's primary objective is to establish an "Islamic State," and its influence has expanded beyond Nigeria into parts of Chad, Niger, and Cameroon (Campbell, 2014). Employing tactics common among terrorist organizations, Boko Haram strategically employs food and income incentives to attract recruits. The group also carries out attacks on civilian populations and vital infrastructure, such as government storage facilities, fertilizer factories, agricultural transport systems, and farms (Adesoji and George, 2019). The epicenter of Boko Haram's activities has been in the rural areas of Borno, Yobe, and Adamawa states. Weak institutional factors, including the existence of ungoverned spaces, lack of employment opportunities, religious extremism, and government instability, have contributed to the group's rise (Kavanagh, 2011; Gassebner & Luechinger, 2011).

The Farmer-herder conflict (FHC) primarily stems from disputes over property rights, specifically the grazing of nomadic herders' animals on farmers' cropland. This interaction leads to crop destruction, prompting farmers to retaliate against herders. The conflict has intensified

as herders move further south into central and southern regions due to increased droughts, desertification, and forced displacement caused by the Boko Haram insurgency. The competition for resources, coupled with religious differences, has exacerbated conflicts over land claims, resource distribution, and control of local administrative authorities (Nanji et al., 2022).

In addition to Boko Haram and the Farmer-herder conflict, Nigeria has experienced a surge in banditry, particularly in the northwest region and some part of the southeast (Akinyetun, 2022). Organized crime and illegal mining activities have contributed to this phenomenon, with a focus on capital accumulation through activities such as kidnapping, armed robbery, murder, rape, cattle rustling, and the exploitation of environmental resources (Osasona, 2023). In the southeast, banditry has mixed with local militias to target oil pipelines and installations (Opejobi, 2016).

The escalation of violent conflict in Nigeria has profoundly disrupted the agri-food value chain. The consequences include decreased production due to land displacement, destruction of fields, restricted physical access to farms, and delays in harvesting, all resulting from the scarcity of human and physical capital (Adelaja and George, 2019). Additionally, agricultural market activities have been severely impacted by terrorist attacks, with recorded incidents disrupting rural agricultural markets and impeding business activities (Van Den Hoek, 2017). Traders and transporters of agricultural goods have also faced challenges, including being held and attacked by armed groups, further hindering the flow of agricultural products (Kah, 2017).

The conflict has led to the displacement of millions of Nigerians, creating a supply-demand mismatch in affected regions and neighboring areas and strained available resources. In turn this has caused food prices to surge significantly in conflict-affected regions. For instance,

after the onset of Boko Haram conflict that displaced 2.3 million Nigerians, the USAID's Famine Early Warning Systems Network reported corn prices in Adamawa increased by 31%, and in Maiduguri, the capital of Borno, prices rose by 25% in January 2017 compared to the previous year (Adelaja & George, 2019). The overall impact is felt across various sectors, with market forces and government initiatives struggling to cope with the demands arising from uncertain population displacements and political changes at different levels (Dunn, 2018).

IV. DATA

To investigate the intricate dynamics between violence and maize prices among traders, we utilize a dataset comprising information from maize traders collected in 2021. The sample is derived from a comprehensive census of maize traders in 63 primary urban maize wholesale markets, strategically located in Ibadan in the South and Jos, Kaduna, Kano, and Katsina in the North (Liverpool-Tasie et al., 2017). The survey encompasses a range of dimensions, including trader characteristics, maize production and processing details, information on procurement and sales, assessments of social and physical capital, as well as distances from traders to their suppliers and clients. Additionally, we factor in distances to main cities and highways to account for urbanization effects.

While the survey was conducted in 2021, we have two observations per trader as our data collected comprehensive information about the transaction between the traders and the suppliers from each trader in both high and low seasons. Our dataset includes crucial details such as the prices paid for different colored maize, the geographical locations of primary suppliers, the distances to these suppliers, and the categorization of suppliers into distinct types, such as farmers, brokers, wholesalers, and more.

To incorporate controls for urbanization, climate variations, institutional factor and exposure to violence, we draw on four distinct sources of data: (1) government-provided data on the population of local government areas or LGA (districts); (2) violence indicators including the presence of NSAA and a violence index computed using Nigeria-specific data from the Armed Conflict Location and Event Data Project (www.acleddata.com), encompassing actors, locations, fatalities, and types of political violence, sexual violence, looting, and property destruction; (3) temperature and rainfall data sourced from the Climate Hazards Group InfraRed Precipitation with Station data, collected by the US government (CHIRPS; <https://data.chc.ucsb.edu/products/CHIRPS-2.0/>); (4) Literacy rates by LGA published by the Nigerian National Bureau of Statistics.

V. CONCEPTUAL FRAMEWORK

i. Main Specification

This paper focuses on the effect of violence on the procurement price paid by traders for the two predominant kinds of maize sold in Nigeria: yellow and white maize. We focus on the price paid by traders to their main supplier during the high season (August 2020-February 2021) and low season (March 2021-July 2021).

In order to estimate the effect of violent conflict we use three different violence measures (at the LGA level) at both the location where traders are based and the location of the transaction (i.e. the main suppliers' location):

1. Number of violent events
2. The number of years of NSAA's presence since 1997
3. A binary variable noting if there was a presence of an NSAA in each season

The first measure (violent events) measures direct violent shocks to an area (attacks, bombs, looting etc.) while the other two measure exposure to NSAA. This distinction is important because being exposed to a NSAA is expected to change the perception that the community has about how often violent shocks will be felt, and on whether or not a region is considered safe. As well, not all traders will directly experience a violent shock, but many are exposed to NSAA, meaning that only accounting for violent events, can underestimate the effects that violent conflict has and how traders respond to it. Thus, we assume that the longer there is NSAA presence in a community, the more likely that people in that community have internalized the associated risks and adjusted their behaviors to account for this

Overall, we expect the effects of a violent shock in a particular season (attacks on farms, bombs etc.) and of exposure to NSAA to be different. While violent events such as destruction of fields and property directly impact physical production, supply, and prices related to that season, exposure to conflict can change production and consumption decisions (Arias et al., 2017). It is important to note that actual violent events might be lower in places where there has been a longer presence of NSAA. If one group has kept control of a territory for a longer time, then there is no need to exert power; whereas places where groups are disputing a territory might have higher levels of violence. These differences make it imperative to separate out the distinct effects of these two types of violent measures when trying to understand the impact of violence on prices. We also include a binary for the presence of NSAA (in addition to the number of years since presence), because in some regions, exposure may have occurred in the past but not in the current season (or even 2021). For example, in Fagge, Kano, between 2012-2014 there were a series of explosive attacks (bombs on buses and churches) by Boko Haram, but there was

no presence of an NSAA group there in 2020 (ACLED). Though long exposure to NSAA has long lasting effects on behavior (Arias et al., 2017), we believe that more recent presence can have a bigger impact on price.

Generally speaking, we also expect that the effects of violent shocks on price will be different than that of exposure, due to how these affect the traders. Violent shocks at their own LGA (like bombing of markets, or road closures) can reduce market access. In this situation, traders will have a harder time leaving their own LGA and in so, reduce their options for supply of maize, making it harder to bargain and therefore observing a higher price of maize. Similarly, higher levels of violence at the main supplier's location can reduce local production through the destruction of farm fields, or the restriction of access to inputs, generating an increase in price. Still, in the case of supplier's LGA, areas that are more violence prone might be experiencing low demand and thus willing to offer their maize at lower prices to traders. This will lead prices to be lower after a violent shock.

This contrasts with the impact of exposure to a Non-State Armed Actor (NSAA), which can lead to behavioral changes. In general, prolonged exposure to violence is associated with adjustments in behavior, as individuals weigh the trade-off between maximizing economic gain and ensuring physical security. In this context, the presence of an NSAA in a trader's home base Local Government Area (LGA) can influence the trader's buying and selling decisions. Traders may opt to source maize from producers or suppliers in safer areas, even if these areas are less efficient in production and have higher prices. Additionally, traders operating in areas with a higher NSAA presence may modify their strategies to mitigate the price hikes or volatility caused by violence. In terms of supplier location, LGAs where NSAA actors are present might have lower

maize prices compared to those where these NSAA actors are absent. This is because increased threat in these areas may reduce demand, as fewer individuals are willing to venture into high-risk zones. Consequently, suppliers may lower prices to attract remaining customers. Given these strategic adjustments, it is crucial to control for the exposure to violence when assessing the actual effects of violent shocks, in order to accurately capture the underlying economic impacts.

It is important to note that we are incorporating violence shock and exposure in both locations because of the mobile nature of traders. Unlike most research that focuses on violence in a victim's residential area, here we address the unique movement patterns of traders. Since we're looking at the specific prices traders pay to their main suppliers, it's important to capture violence in the specific locations where transactions occur, as traders are directly impacted by the conditions they encounter in these regions. Our sample includes traders from both northern and southern Nigeria, who source maize from various regions across the country. Given that violence is most prevalent in the north, with some hotspots in the south, it's important to capture this geographic variability.

To measure violent shocks at both locations, we examine four variables representing the number of violent events in each season across LGAs. Each variable reflects a specific type of violent event. By categorizing violence in this way, we aim to analyze the relative effects of different types of violent activity. The four categories are:

1. Number of armed confrontations in each LGA: This category captures violent events involving at least two armed, organized groups, such as military forces and insurgent groups like Boko Haram. It includes incidents like armed clashes or instances where a non-state actor seizes control of a territory.

2. Number of explosions/remote violence in each LGA: These include one sided event where explosive devices were used. It includes attacks with bombs, grenades, improvised explosive devices (IEDs), artillery fire or shelling, missile attacks, heavy machine gunfire, air drone strikes, or chemical weapons
3. Number of events of violence against civilians: This category accounts for incidents where an organized armed group deliberately targets unarmed civilians. This variable includes sexual violence, attacks, abduction/forced disappearance.
4. Strategic developments: These variable captures significant events that may influence political dynamics or future conflict. It includes occurrences such as arrests, the disruption of weapons usage, and looting or property destruction. Since these events are less frequent, they are coded as a binary variable (1 if such an event occurred).

In order to obtain the four variables, we used data from the Armed Conflict Location & Event Data Project (ACLED) which has the most comprehensive disaggregated information on political violence events. ACLED records different political violent and non-violent events (by date) which are then classified into six different event types and 25 sub-event types. We focused on the violent events that were recorded in the region during each season.

We hypothesize that traders in LGAs with higher levels of violence will generally face higher prices, as violence limits their market access and reduces available purchasing options. However, these effects may vary depending on both the type of violence and the type of maize (yellow or white). For example, armed confrontations and explosions typically lead to the destruction of production facilities, resources, and homes, resulting in higher prices due to production shocks. In contrast, violence against civilians or strategic developments could lower

prices by reducing demand, as maize buyers—whether traders or other consumers—may avoid markets out of fear of targeted attacks.

With regards to the type of maize, since white maize is used for human consumption and yellow maize is used for animal feed, the effect of violence could be different. Specifically, we expect white maize to be more sensitive to violence shock as it is considered a staple food. Specifically, we anticipate that white maize, as a staple food, will be more sensitive to violence-induced shocks. In general, higher violence shocks are likely to cause price spikes since demand remains relatively stable, but if production is disrupted, this is likely to impact other staple agricultural products grown in those agroecological zones, limiting substitution options. Yellow maize, on the other hand, might be less affected by production shocks if livestock can continue grazing on pastures. However, if violence, especially from FHC attacks, spreads into rural areas where pastures are located, this may restrict feed availability. Such disruptions could both increase demand for maize feed and limit its supply, ultimately driving up prices.

In the case of the location of the main supplier (i.e. the main supplier's LGA), the effect of a higher violence index can be both negative or positive. From the literature we know that violence can generate changes in production and use of technology in a specific area, which in turn increase the price of maize (due to lower supply). At the same time, farmers in areas that are more violence prone might be experiencing low demand and thus willing to offer their maize at lower prices to traders.

To estimate exposure to violent actors we use the ACLED data set to calculate the number of years of presence of a NSAA has had in a territory since 1997. As well, we constructed a binary variable that indicates if there was a NSAA in a specific LGA in each season. Again, we compute

these two variables for both the LGA of the traders main trading base, as well as the LGA where the traders main supplier is located. Overall, a longer presence of a NSAA within a territory can modify the behavior of both traders and suppliers. We assume that over time, as non-state armed actors extend their stay in the community, traders and suppliers are more inclined to believe that these actors will establish dominance in their region, and that shocks will be more permanent. This will then lead to changes in behavior that will allow those affected to smoothen the impact of these shocks. We also include a variable that captures if there was presence of an NSAA in a season because there are LGAs that had NSAA in the past but not within the seasons (or even 2021), reducing the effect that the NSAA could have.

We hypothesize that a longer presence of NSAA in both the trader's and suppliers' LGA will have a mediating effect on price shocks (caused by violent events) such that prices will be lower relative to areas with shorter exposure to NSAA. Literature notes that households in violent regions learn to cope with violence over time and can smoothen their consumption (George et al., 2020 and D'Souza and Jolliffe, 2013). Traders that have been exposed to conflict for a longer time are thus likely to be better adapted to manage violent events and keep their input prices low. Whereas traders that are suddenly exposed to violence have not learned to cope and will then experience higher prices.

Thus far, we have only addressed the impact of violent shocks in the season where the maize trade transaction was made. However, lingering effects of past violence shocks may persist and play a role in shaping prevailing prices. For example, a disturbance in the previous season is likely to operate as a supply shock, affecting maize production and availability. To address this, we also include four additional lagged violence indicators. The first two are the lagged presence

of NSAA at the trader's own and main supplier location. The second and third are a lagged violence index (described below) for the trader's LGA and for the main supplier's LGA. It should be emphasized that these lagged variables are calculated by season, meaning that the lagged violence indicator for a transaction in the high trading season (August 2020-February 2021) is the violence indicator for the previous season (March 2020-July 2020), and the lagged violence indicator for a transaction in the low trading season (March 2021-July 2021) is the violence indicator for the previous high trading season of August 2020-February 2021.

The index was created for each LGA following Ferguson, Hiler and Ibañez (2018). Since we are already including disaggregated measures of violence, to prevent any type of correlation, this index allows us to capture the lingering effects of many types of violence associated with NSAA. The index is constructed for each LGA as follows:

$$Violence\ Index = \frac{1}{|I|} \sum_{i \in I} (v_i - \bar{v}_i) / (\sigma_i)$$

Where $|I|$ is the number of variables used for the violence index. v_i is the number of event types of variable i (capturing a violence event type, like attacks) in a specific LGA. $\bar{v}_i$ is the mean across LGAs of the number of those events per year, and σ_i is the standard deviation of v_i across LGAs.

In order to obtain the different components for the violence index, we again used data from the Armed Conflict Location & Event Data Project (ACLED). For the construction of the index, we are focusing on violent events that happened in the previous season. More specifically we use the following types of events:

1. Armed clash

2. Non-state actor overtakes territory
3. Air/drone strike
4. Suicide bomb
5. Shelling/artillery/missile attack
6. Remote explosive/landmine/IED
7. Grenade
8. Sexual violence
9. Attack (an event in which civilians are targeted with violence by an organized armed group)
10. Abduction/forced disappearance
11. Arrests (This type of event refers to instances where state forces or other groups with de facto control over a territory either arrest a key individual or carry out mass detentions.)
12. Disrupted weapons use
13. Looting/property destruction

These 13 events represent the different i 's within the index (meaning $I = 13$ in a year where all these events were recorded). In the ACLED data set, these events are recorded by date. If an event lasted more than a day then each day is recorded as a separate event. In order to construct the variables, we calculated the number of events by type within an LGA for each season. This is what the v_i is representing: the number of events by type per season. The violence index basically reflects how the violent events within a specific LGAs compare to other LGAs in the country. In this case, LGAs with a negative number had less violent events in comparison to

the others. LGA's with an index around 0 are at the mean of violence in the country and those LGAs with an index value above 1 have extreme levels.

As with the main specification we hypothesize that the lagged presence of NSAA actors at both the main suppliers' and the traders' LGA will have a mitigating effect on price shocks as traders that have been exposed to conflict for a longer time are thus likely to be better adapted to manage violent events and keep their input prices low. With regards to the violence index, the effect on price can either be positive or negative. Lagged violence indexes at the traders' and suppliers' LGAs can have a positive relationship with price, as more intense shocks can lead to both limited market access and a supply shock that reduces the overall quantity of maize for the next season. On the other hand, lagged violence indexes can serve as indicators of past exposure to shocks, making it so that there as fall in demand causing prices to drop.

We recognize that violent actors do not select territories arbitrarily; rather, non-state actors strategically position themselves in areas characterized by specific geographical and institutional features that align with their overarching objectives. To accommodate this, we incorporate both temperature and rainfall data for each local government area (at both the traders' and suppliers' LGAs). These variables function as indicators of regions with different productive resources owing to heterogeneous weather conditions (e.g. adverse weather), potentially prompting an increase in violence as a means to secure economic resources. Furthermore, emerging research, such as Raleigh et al. (2015), has drawn connections between violent conflict and environmental factors, indicating that abnormal dry conditions are associated with increased conflict frequencies. We also include variables to control for the specific seasons with the high season, stretching from August to February, and the low season, from March to

July. The trading seasons align with Nigeria's dry and rainy seasons, suggesting a possible connection between violence and these climatic periods.

With regards to institutional factors, we include two different variables, first a dummy variable that indicates whether or not an LGA is the capital of that state (for both the traders' and suppliers' LGAs). As well, we include the literacy rates per LGA, published by the Nigerian National Bureau of Statistics. These metrics, identify areas with heightened vulnerabilities and lower institutional organization, which are often targeted by non-state armed actors (NSAA).

A potential problem when estimating the impact of violence on maize prices is reverse causality. Many studies have identified food insecurity as a conflict trigger. These papers identify key variables associated with food insecurity that contribute to conflict, such as food price shocks (Fjelde 2015). Bellemare (2015) and Hendrix and Haggard (2015) link global food prices with food-related riots and urban unrest, gauged through protests, demonstrations, and violence. In the case of Nigeria, the situation is different as the violence has stemmed from attacks by Boko Haram, FHC and banditry and very little by riots or protests. From the ACLED data set, out of all the violent events from 1997-2022, only 5% were violent demonstrations and 5% were mob violence. From both peaceful and violent demonstrations, only a handful were related to food, and most of these took place within refugee camps in Borno. The protests that were related to price, most commonly were focused on the increase price of fuel. Still, membership in Boko Haram and the sustainability of their activities may be closely related with poverty and food insecurity. Individuals experiencing hunger and economic hardship are vulnerable targets for recruitment. Moreover, areas characterized by poverty and food scarcity are likely hotspots for increased violence and theft, creating an environment conducive to the activities of groups like

Boko Haram. We believe that our geographical and institutional variables partly control for these. Given the potential relationship between places with social and economic vulnerability and increased activities of NSAA, including the number of years of NSAA presence may be controlling for regions with historical poverty. Because of this interplay, we interpret our findings as important correlations but do not claim causality.

Since access to market and market dynamics can determine the bargaining power and hence price paid by traders, we utilize four distinct variables to control for market access. The first is the distance between the trader's main location and the nearest capital city. If traders are closer to a capital city (largely a consumption area), then they are likely to have access to more buyers than their counterparts located far from the capital city. The distance of traders to a city also captures the trader's access to other maize suppliers (especially other wholesalers and brokers). Being in (or close to) an area with more suppliers to choose from enhances traders' bargaining power and ability to negotiate lower prices. On one hand traders with easier access to many buyers and suppliers might be more able to internalize the payment of higher prices for maize since they face a larger market and lower search costs operating from a location in/close to a major consumption area.

The second market access variable we include is the distance between the location of the trader's main supplier and the closest capital city. The effect that this distance has on prices can be ambiguous. Suppliers (particularly farmers) that are closer to a city typically have better access to inputs and technology often at lower prices (Haggblade et al; Vandercasteelen, Beyene, Minten, & Swinnen, 2018). Such farmers might be able to accept lower sales price to cover their costs of production compared to their counterparts who are more remotely located and face

higher production costs. This could allow traders to get maize at lower prices from farmers that are closer to a capital city. Moreover, it could also be argued that suppliers closer to the capital city (largely a consumption area) might face more competition from other suppliers targeting the consumption area which then lowers the price traders have to pay to be competitive.

However, if the procurement location for a trader is closer to a bigger city, it is also possible that such suppliers also have access to more buyers which increases their trading options and could lower the traders' bargaining power and increase price paid. It is also possible that procuring from a supplier who is closer to the capital city lowers the transportation and transactions cost of procuring from the farmer, meaning traders can offer higher prices. For this reason, we consider the impact of the distance between the main supplier's LGA and the capital city to be an important determinant of prices but whose direction is theoretically ambiguous.

The third and fourth market access variable we explore is the urban density of the local government area where the trader is located and the LGA of where the main supplier is located. These variables signify how big the potential market is, which in turn increases the number of suppliers and the likely availability of different types of maize. Overall, we expect LGAs with higher density of population to have lower supply prices as there is likely to be larger number of suppliers and buyers, giving traders more bargaining tools. Nonetheless, there is a possibility that prices are lower in less populated areas, as suppliers might be willing to lower their prices in order to attract more buyers.

There is a documented relationship between urbanization and violent conflict (Stenhub and Minten, 2023), but it is not always straightforward and is context specific. Violent conflict occurs in both remote and highly urbanized settings. For example, NSAA (especially those trying

to overthrow the government) might prefer highly urbanized areas as controlling for significant economic, cultural, or political centers is often crucial for challenging authority and asserting legitimacy as the ruling party. George et al. (2020) show that conflict events tend to occur more frequently in urban areas due to this reason. However, in different contexts, conflict actors may prefer remote areas as they are easier to control (Arias et al., 2019).

In the case of Nigeria, Van Den Hoek (2017) notes that markets are prime venues for targeting civilians. Boko Haram attacks seem to be well timed to disrupt agricultural production, with the peak period of attacks immediately preceding the lean season and then reaching a secondary peak just at the harvest's conclusion. The timing of these attacks seems almost designed to deter agricultural labor as well as the transport of agricultural goods to market. To control for this relationship, we include an interaction between the violence index and urban density at all locations. A positive relationship between this interaction and prices would reflect that the effect of violence on price is bigger on larger urban centers. Where a negative effect would indicate that the effect of violence of price is bigger in more rural areas.

We also control for transaction characteristics such as the type of supplier (individual farmers, farmer groups/associations/cooperatives, rural traders, other urban wholesalers and brokers), the location of the main supplier (north or south of Nigeria), and if the trader picked up the maize from the main supplier. Overall, we expect that farmers have the lowest prices in comparison to others as they normally don't incur in shipping and handling costs. As well, we expect traders who pick up the maize obtain lower prices as they are incurring in transport costs. It is important to note that we did not include moisture level within our transaction variables as 92% of the traders buy their maize dry.

The location of the main supplier (north vs south) controls for variation across production areas. Though maize is grown in all of the country, the biggest production region is the North. Where 9 northern states represent 58% of all maize production in Nigeria (PWC, 2021). Still, the South of Nigeria has a higher population density and is home to many large consumption areas such as Lagos, Port Harcourt and Enugu. The South is also generally more affluent than the north. These differences make it hard to predict the effect in price. Being in a production area can decrease the price of supply that is paid by the traders, particularly if it is an area with many other suppliers. Nonetheless, being in a higher populated area can also mean access to different types of suppliers.

We also include a set of trader characteristics such as size, gender, religion, age, level of formal education, the location of the market (rural vs urban) and experience with trading maize. Size is measured using two variables: size of production and number of stalls. For the first variable, we categorized traders as large if they sold 32 tons (or more) per month within the high season and small if they sold less than 32 tons. The second variable is the number of stalls (rented or owned) that the traders have both in markets and in off market locations. We also include a variable for social capital (a one-zero variable that indicates if the trader is part of an association) and control for whether the trader grows their own maize. We expect social capital and growing your own maize to have a negative relationship with price. Associations can collectively negotiate for better prices, and growing maize can make the trader less dependent on their suppliers, increasing their bargaining power.

VI. EMPIRICAL STRATEGY

We estimate the following equation (separately for white maize and yellow maize) to understand the relationship between violence levels (at a traders' location and the location of the traders' main suppliers) and prices paid by traders.

$$\begin{aligned} (MP_{i,j,k}) = & \gamma + \beta_{vo} \mathbf{ExpO}_{ik} + \beta_{vs} \mathbf{ExpS}_{ik} + \beta_{vio} \mathbf{NVE_O}_{i,k} + \beta_{vis} \mathbf{NVE_S}_{i,k} + \delta_{vio} (VI_O_{i,k} * \\ & \mathit{demeaned}_{Urban\ density_i}) + \delta_{vis} (VI_{S_{i,k}} * \mathit{demeaned}_{Urban\ density_i}) + \theta_{vio} VI_O_{i,k-1} + \\ & \theta_{vis} VI_S_{i,k-1} + \theta_{po} \mathit{presence_own}_{i,k-1} + \theta_{ps} \mathit{presence_supp}_{i,k-1} + \beta_{tec} \mathbf{TEC}_{ik} + \\ & \beta_{trc} \mathbf{TRC}_{ik} + \beta_{sc} \mathbf{STC}_{ik} + \beta_s \mathit{season} + C_i + e_{ijk} \quad [1] \end{aligned}$$

Where $MP_{i,j,k}$ is the price paid in Naira per bag (each bag is 100kg) by trader i in season k (low season or high season) for maize of color, j , (white or yellow) to their main supplier. This price depends on a series of variables and vectors (vector are in bold). First it includes two vectors to control for exposure to NSAA at the local government level (LGA) of the traders' own main location ($\mathbf{ExpO}_{ik}$) and exposure to NSAA at the main suppliers' LGA ($\mathbf{ExpS}_{ik}$). These vectors include the number of years of presence of non-state armed actor (NSAA) since 1997 and a dummy variable indicating whether there was presence of an NSAA in season k in the trader's own and supply LGAs respectively.

Maize price also depends on a vector that includes the number of violent events in season k for the trader's own LGA ($\mathbf{NVE_O}_{i,k}$) and main suppliers LGA ($\mathbf{NVE_S}_{i,k}$). These vectors include the variables: number of armed confrontations in each LGA, number of explosions/remote violence in each LGA, number of events of violence against civilians, and strategic developments (binary). We also include $VI_O_{i,k} * \mathit{demeaned}_{Urban\ density_i}$ and $VI_{S_{i,k}} * \mathit{demeaned}_{Urban\ density_i}$ as interaction terms between the violence index and urban density at

the traders own LGA and suppliers LGA respectively. In this interaction, urban density is demeaned to avoid including the unlikely situation of zero urban density.

We control, as well, for four lagged violence variables: lagged presence of NSAA in a traders' LGA ($presence_own_{i,k-1}$) and in suppliers LGA ($presence_supp_{i,k-1}$), and lagged violence index in the traders' LGA ($VI_O_{i,k-1}$) and in the suppliers' LGA ($VI_S_{i,k-1}$).

We also include a vector (TEC_i) which is made up of territorial, institutional and market access control variables at both the traders' main LGA as well as the location of their suppliers. This vector includes two types of controls. One, territorial and institutional variables at both the traders' and suppliers' LGA such as average daily rainfall (mm) and average daily temperatures (C°) in 2020 at the LGA levels, literacy rates per LGA, and a dummy that indicates whether the LGA is a capital. Two, market size by using the urban density (population per km²) in 2020 and the distances from LGAs to the closest capital from both the suppliers' and traders' LGAs. It is important to note that all of the variables at the suppliers' LGA are time-variant, as the location of supplier's changes in the cases in which traders changed suppliers. Nonetheless, some of the locational characteristics of the traders' own LGA do not change in each season as traders did not change location by season and these characteristics did not change (for example urban density, literacy rates, distances and if the location is a capital).

TRC_{ik} is a vector of trader characteristics. These include size, gender, the location of their main market (rural vs urban), education, age, and experience. Size is measured by two variables, the amount sold and the number of stalls. Where large traders are those that sold 32 tons (or more) per month within the high season. The second variable is the number of stalls (rented or owned) that the traders have both in markets and off markets. We also include a variable for

social capital (a dummy that indicates if the trader is part of an association) and if the trader grows their own maize.

STC_{ik} is a vector of transaction characteristics. Here, we include information on the type of supplier, the location of the main supplier (north or south of Nigeria), the distance in Km to the main supplier, and if the trader picked up the maize from the main supplier. We also include a variable to distinguish each season (*season*). e_{ijk} is a vector of idiosyncratic errors and C_i , are individual heterogeneity that is unobserved.

In order to estimate equation 1, we need to account for the individual heterogeneity. To do so, we employ a correlated random effects model (CRE), using a Mundlak approach as described by Wooldridge (2010). Where we model the relationship between C_i and our dependent variables as follows:

$$C_i = \psi + \bar{x}_i\xi + a_i$$

Where $\bar{x}_i$ is a vector of the mean of all time variant independent variables in equation 1, and a_i has zero mean and is assumed to be uncorrelated with all of the independent variables. We decide to use this approach because it allows us to include time-invariant explanatory variables in the model (such as number of years of NSAA presence). As well, with this method we are not assuming that C_i is not correlated with the explanatory variables. This is important as it is likely that trader individual unobserved heterogeneity is correlated to their place of residence and trading characteristics.

VII. DESCRIPTIVE STATISTICS

This section presents descriptive statistics to describe how and where the maize traders in our sample are operating, who they are selling to, the maize's prices paid, transaction characteristics and the distribution of violent conflict among traders in our sample.

Table 3.1 provides an overview of the traders in our sample, revealing key characteristics relevant to their roles in the maize market. A significant portion (68%) of the traders are large farmers, selling over 32 tons of maize. On average traders have 1 stall and only 28% of stalls are located in urban markets. Female representation among traders is low at just 12%. Over half of the traders (56%) are part of an association, which may facilitate collective bargaining and access to resources. On average, traders have 20 years of experience and are 46 years old. Most traders (93%) are based in the North, with only 7% in the South, reflecting the concentration of maize production in the northern region.

Table 3.1: General Trader Characteristics

Trader Characteristics	Mean
% Large traders	68%
Number of stalls	1
% Female traders	12%
% Located in urban markets	28%
% Part of an association	56%
Years of experience	20.1
Age	46.4
% Traders located in the South	7%
Total Number of traders	1,111

Table 3.2 presents key characteristics of main maize suppliers categorized by the high and low seasons. We differentiate by season as traders also change suppliers across seasons. The comparison between the trader's main maize suppliers across high and low seasons reveals, the

dominance of individual farmers as the primary source of maize throughout both periods, but significantly more in the high season (source for 66% of traders) compared to the low season (54%). We also see a significant rise in the relative importance of rural traders in the low trading season (33%) compared to the high trading season (22%) when maize is more abundant. This increased reliance on rural traders during the low season suggests their crucial role in the maize supply chain during periods of decreased maize availability.

The data in table 3.2 also indicates that the majority of traders rely on a limited number of supplier types, with a significant portion sourcing from only one or two types. In the high season, 78.7% of traders (37.7% with one source and 41% with two sources) obtain maize from just one or two supplier types. This trend is similar in the low season, with 80.9% of traders (42.9% with one source and 38% with two sources) sticking to one or two types. This reliance on a small number of suppliers, primarily individual farmers, reinforces that transactions typically occur directly at the farm level, minimizing intermediaries

Table 3.2 also confirms the dominance of maize supply from northern Nigeria (accounting for between 96% and 99% across the high and low trading seasons respectively). The low share of traders (4%) that have their primary suppliers in the south are from Oyo (located in the south), meaning that these traders most probably source from the south to reduce their transportation costs. These findings are not surprising given that the North serves as a major hub for maize cultivation, where roughly 9 northern states represent 58% of all maize production in Nigeria (PWC, 2021).

Table 3.2: Main supplier characteristics by season

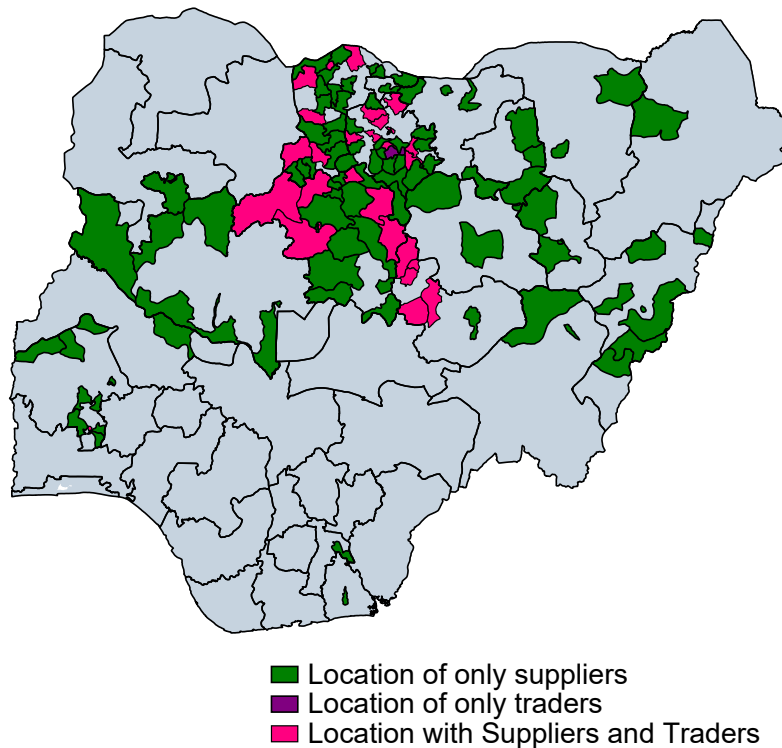
	High Season	Low Season
% of traders whose main supplier is:		
An individual farmer	66	54
A farmer group/association/cooperative	1	1
A rural trader	22	33
Another urban wholesaler	4	6
A broker	7	7
Number types of sources (%)		
1 source	37.7	42.9
2 sources	41	38
3 sources	17	16
4 sources	4	2
5 sources	0.1	0.2
6 sources	0.5	0.4
% of traders whose main supplier is in the:		
North	96	99.8
South	4	0.2
% of traders who procured maize from:		
The same LGA where they are based	26	24
The same State but a different LGA	26	20
Out of state	48	56
Average distance to Main Suppliers (km)	131	154
Total Number of traders	1,111	1,111

Source: Authors' calculations

Table 3.2 also reveals a dual pattern of local and interstate transactions. While a non-trivial proportion of trader's source from their own LGA and state (26% each in the high season), a substantial number (and a majority) source from suppliers located in other states; 48% and 56% for the high and low seasons respectively. This highlights the diverse nature of sourcing strategies of maize traders in Nigeria, with many needing to cross state boundaries for their maize supplies. This emphasizes the need for certain traders to navigate longer distances in pursuit of maize

supplies which likely exposes them to violence at numerous points along the maize supply chain that can delay or reduce mobility of traders, especially for traders in the south.

Figure 3.1: Location of Traders and Suppliers



Source: Authors' calculations

Figure 3.1 illustrates the geographical spread of maize traders and suppliers across Nigeria. Traders (highlighted in pink and purple) are located in several regions, predominantly in the north and central areas, with some overlap with supplier locations (pink) but also spanning areas with only suppliers (in green). The map shows that most trading relationships require significant distances to be covered, as traders often source from various parts of the country. This spatial distribution highlights the logistical challenges in the maize trade, with traders regularly moving across considerable distances to source their goods. The overlap between

trader and supplier locations in some regions, shown in both pink and green, further emphasizes the interconnected nature of these regions within the supply chain.

Table 3.3 presents maize mean prices paid by traders categorized by type (yellow and white) across two seasons—low and high as well as the average for both seasons. Prices are reported in naira per 100kg bags. As well, we include the percentage of traders that reported buying maize by type. In this table two key points stand out. First, we find that white maize is the most popular among traders. Despite the price difference, white maize maintains a remarkably higher percentage of trader involvement at 94% as opposed to yellow maize's 54%. This is surprising as 45.5% of maize produced in Nigeria is used for animal feed, but white maize is solely for human consumption while yellow is used for both (PWC, 2021). This suggests that yellow maize attracts a more specialized group of traders that focus on feed for cattle and poultry or that some feed millers (likely large feed companies) might also directly source from farmers themselves. This implies that there are a few traders that obtain both from their main suppliers. In fact, from the data, we know that around 50% of traders buy both in each season.

Second, there is a significant price difference between seasons, but the share of traders is consistent across types of maize. Yellow maize exhibits a price increase from 15,671 naira in the high season to 22,265 naira in the low season, with a consistent percentage of traders. Similarly, white maize experiences an increase from 16,174 naira to 21,383 naira, maintaining a stable trader involvement percentage.

Overall, during the high season there is a bigger production of maize in general, which would in turn make maize prices go down. Whereas the low season there is less production, leading prices to go up. As well, the fact that the percentage of traders remains the same across

seasons implies that the demand for each remains steady. A t-test conducted for each maize type by season determined that the difference in means was statistically significant at the 1% level for both yellow and white maize.

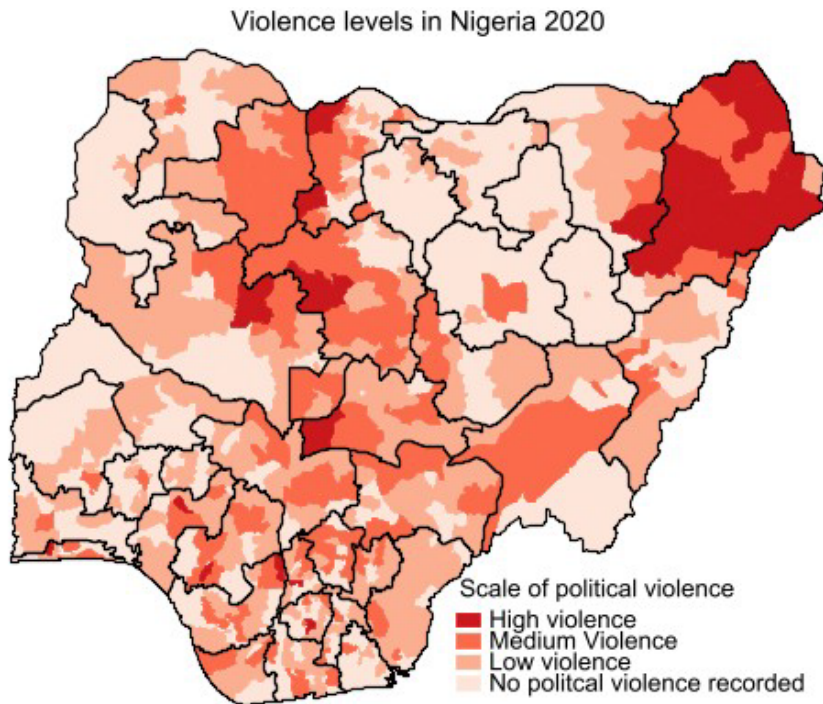
Table 3.3: Mean maize prices and percent of traders that sold maize by type

	High Season			Low Season			Average Season		
	Price naira	St. Dev	% traders	Price naira	St. Dev	% traders	Price naira	St. Dev	% traders
Maize standardized to 100kg bags:									
Yellow Maize	15,671	6,315	53	22,265	10,920	54	18,925	9,524	57
White Maize	16,174	8,239	94	21,383	4,939	94	18,763	7,276	96
Any color	15,935	5,600	100	21,546	6,351	97	18,711	6,613	100
Number of traders	1,111			1,111			2,222		

*Source: Authors' calculations

Figures 3.2, 3.3(a) and 3.3(b) and Tables 3.4 and 3.5 present the distribution of violent conflict and how it relates to the traders. Figure 3.1 shows the scale of violence per LGA in all of Nigeria. The figure was constructed using the violence index and then categorizing it as “Low violence”, “Medium Violence” and “High Violence”. Where a violence index of <0 was considered “Low Violence”, between 0-1 “Medium Violence”, and >1 “High Violence”. Figure 3.1 clearly reveals that violence is quite widespread across Nigeria with highest intensity in the north, particularly the northeast (Borno state) followed by the northwest (Katsina and Kaduna states) and then the Middlebelt region (Nassarawa state). This is not surprising as both Boko Haram and the FHC have more presence in the North but have started to move southward. As well, banditry is also very common in both regions, and has intensified in the South.

Figure 3.2: Violence Levels in Nigeria 2020 based on the levels of Violence Index



Source: Authors' calculations. Where a violence index of <0 was considered "Low Violence", between 0-1 "Medium Violence" and >1 "High Violence"

Figure 3.3: Violence Levels in the trader's and suppliers' location for all seasons in 2020, based on the levels of Violence Index

(a). Violence levels at location of traders

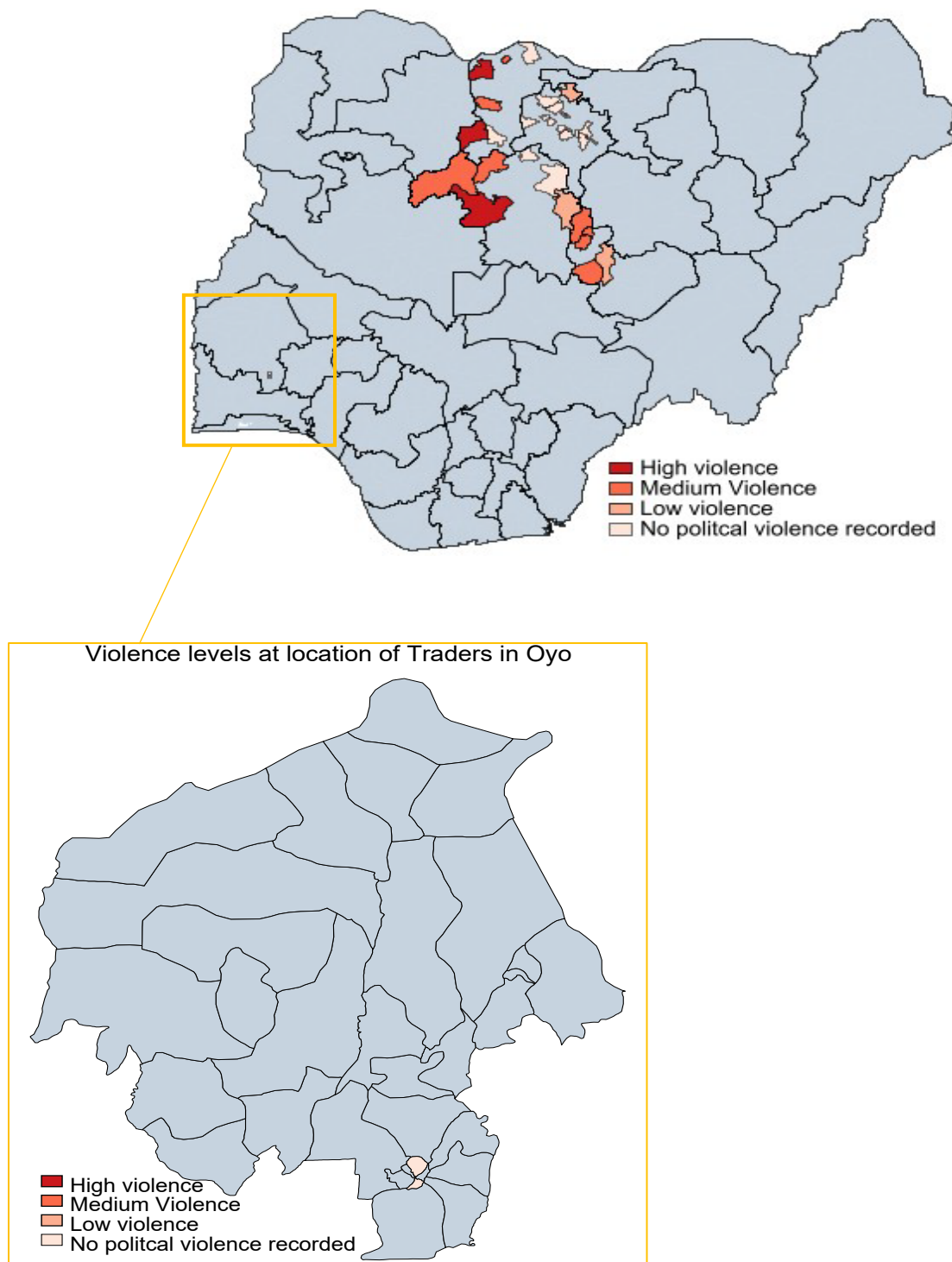
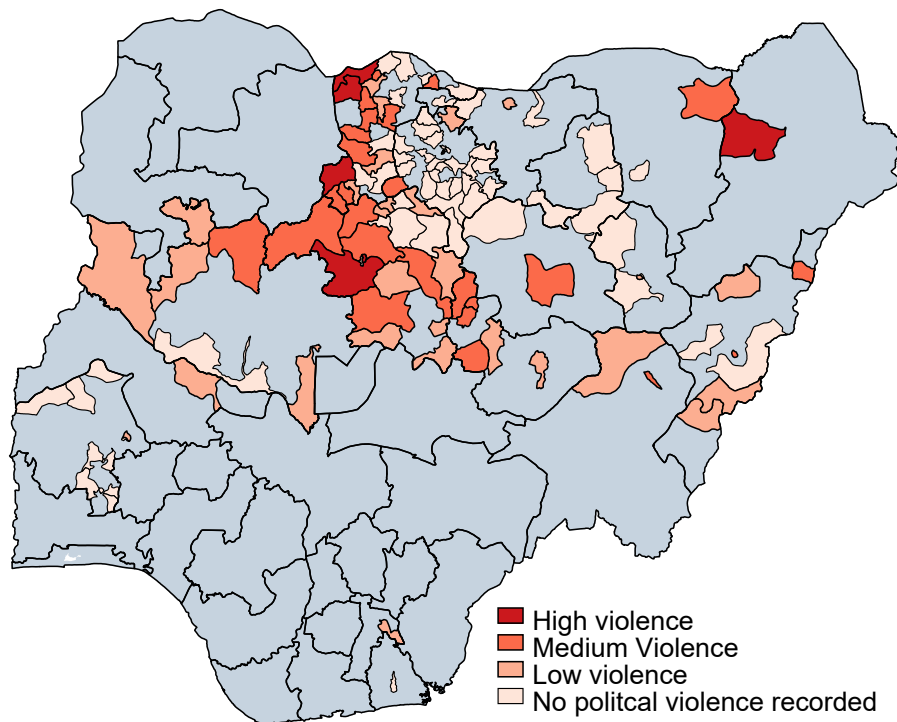


Figure 3.3 (cont'd)

(b). Violence levels at location of suppliers



Source: Authors' calculations. Where a violence index of <0 was considered "Low Violence", between 0-1 "Medium Violence" and >1 "High Violence"

Figure 3.3 presents violence levels for the LGAs where the traders in our sample are located (3.3a) and the violence levels for the LGA of the main suppliers (3.3b). Figure 3.2 clearly shows that there is a wider dispersion of locations for maize suppliers compared to the traders. This is not surprising as it reflects the need for traders to source for maize beyond their trading locations to secure the maize needed to supply their customers. Comparing Figure 3.3a and Fig. 3.3b reveals that even if maize traders are located in areas with low violence (e.g. Oyo), traders are still exposed to shocks beyond those at their trading base when sourcing their maize from suppliers. This demonstrates the critical importance of paying attention to violence and other

shocks along the entire trading route when exploring a trader's exposure to shocks and their impact on their operations and subsequently on the entire supply chain for maize in Nigeria.

Table 3.4 describes how violence measures are distributed across traders and their main suppliers' LGAs. We included the seasonality for the suppliers' LGAs as trader's supplier location often changes across seasons. This means that an increase in violence levels across seasons implies that traders are sourcing from more violent regions. From table 3.3 we can see that in 2020 in both season, 33%-31% of traders experienced NSAA presence in their own LGAs while even higher levels of violence are noted in their suppliers' LGA (46% and 62% for the high and low season respectively). This clearly reveals the substantial exposure of maize traders to violence in their maize trading activities, especially when sourcing during the low season. The lower percentage of supplier LGAs with presence of NSAA during the high season compared to the low season reflects likely seasonality in conflict dynamics and/or the need for traders to travel to more dangerous areas in order to obtain the supply that they need during periods of lower supply.

Table 3.4: Violence indicators at the trader's and suppliers' location by season

Violence Measures	Trader's own LGA		Main Supplier's LGA	
	High Season	Low Season	High Season	Low Season
Presence of NSAA in 2020	33%	31%	46%	62%
Mean number of years of NSAA presence	3.27	3.27	3.35	3.67
% Traders that experienced a:				
Armed Confrontation	26%	28.3%	59%	40%
Explosion	6%	20.3%	8%	24%
Violence against civilians	21.1%	32.7%	28%	44%
Strategic development	6.1%	2.4%	7%	2%
Total Number of Traders	1,111	1,111	1,096	1,098

*Source: Authors' calculations

In table 3.4 we see that suppliers' LGAs experience higher levels of violence across categories. Notably, violent events in traders' own LGAs are more common during the low season, while violence spikes in the high season in suppliers' LGAs. This seasonal variation makes sense given the higher trading activity during the high season at suppliers' locations, where disruptions can have more immediate impacts on the maize market.

The data also suggest that a higher NSAA presence does not necessarily correspond to increased violence. For instance, traders' own LGAs report a similar number of years with NSAA presence but experience fewer incidents compared to suppliers' LGAs, where presence and violent events differ significantly by season. This inverse relationship underscores that the presence of NSAAs alone doesn't predict the intensity of violence, indicating that other local dynamics may play a role in the escalation or suppression of conflict events. As well, it likely reflects the broader increase in conflict and violence occurring across the country, which may amplify the risks in certain regions regardless of NSAA presence

Table 3.5: Mean Prices of Maize by violence levels at traders own LGA and main suppliers LGA

Price (Naira per 100 kg bag)	2020 Violence Levels at					
	Trader's own LGA			Main Supplier's LGA		
	Low	Mid	High	Low	Mid	High
High season						
Price Yellow Maize	15,958	13,624	18,628	15,595	15,374	18,020
Price White Maize	16,304	14,309	18,371	16,025	16,354	17,598
Total Number of traders	745	265	101	792	229	90
Low season						
Price Yellow Maize	22,001	22,503	24,087	21,720	22,803	25,860
Price White Maize	21,463	20,298	23,047	21,343	21,357	22,652
Total Number of traders	904	178	29	792	229	90

Source: Authors' calculations

Table 3.5 presents mean maize prices per 100 kg bag during both high and low seasons, categorized by different levels of violence at traders' own LGAs and their main suppliers' LGA. In the high season, variations in prices are evident across different violence levels. For yellow maize, prices range from 15,958 Naira in LGAs with low violence to 18,628 Naira in LGAs with high violence. Similarly, white maize prices vary from 16,304 Naira to 18,371 Naira across low to high violence levels. During the low season, prices exhibit similar variability. Yellow maize prices range from 22,001 Naira in low violence LGAs to 24,087 Naira in high violence LGAs. White maize prices show a range from 21,463 Naira to 23,047 Naira across the same violence levels.

What is surprising is that while the mean price is consistently increasing with violence levels in the main supplier's region, mean prices in the traders own LGA are not consistently increasing with violence levels but actually show a U-shaped relationship with prices lower at regions of mid-level violence compared to locations with low or high levels of violence. As well, we observe that this relationship holds consistently for both yellow and white maize during the high season, but only for white maize during the low season. However, it consistently remains positive in the main suppliers' region for both seasons and products. This could potentially indicate that the relationship with violence is not linear and can change based on the season. Still, given the differences, we still assumed the relationship to be linear. Especially since independent of the season, the most violent areas had the highest prices.

VIII. RESULTS

Table 3.6 presents the results from estimating Equation 1, which identifies the factors influencing traders' procurement prices for white and yellow maize. Eight key points stand out. First, there is a strong and economically significant effect of violence on maize procurement prices for

Nigerian traders, but it varies by the type of violence. As expected, armed confrontation and explosions have a positive effect on prices. Specifically, each additional armed confrontation event is associated with a higher maize price of N334.32 (for white maize) and N630.56 (for yellow maize) all else equal with both effects statistically significant at 1%. For explosions, each additional event is related with a raise in yellow maize prices of N143.41 (also significant at 1%), but has no effect on white maize. These violent events disrupt production by destroying property, products, and inputs, creating production pressures that drive prices up.

Conversely, violence against civilians has a negative relationship with prices, likely by reducing demand. This type of violence may discourage maize buyers, including traders and consumers, from visiting markets out of concern for their safety. Violence against civilians has the strongest impact amongst all types of violence within a season, affecting prices in both the trader's own LGA and that of the supplier. Specifically, for white maize, each additional civilian-directed violent event is associated with a decreases prices by N365.74 in the trader's LGA and N475.86 in the supplier's LGA (both significant at the 1% level). For yellow maize, this same change is related to significant price decreases of N135.43 and N766.51 in the trader's and supplier's LGAs, respectively.

A second key point from the regression estimates (Table 3.6) is that overall, violence shocks within the same season similarly impact both yellow and white maize prices, but in opposite directions. The most significant difference lies in the effect of strategic developments. In the trader's own LGA, a strategic development event (i.e. looting and arrests) is associated with increases in white maize prices by N7,001.68, but has no relationship with yellow maize prices. Conversely, a strategic development in the supplier's LGA is associated with a decrease in

yellow maize prices by N2,601.47, but not significant with white. One potential explanation for this pattern is the difference in production and sourcing dynamics between the two maize types. White maize production may be more geographically restricted, while yellow maize production is more widely distributed. This limitation in white maize sourcing options means that production shocks can drive up prices, as buyers have fewer alternative locations to source from. On the other hand, the broader availability of yellow maize allows buyers to shift to other, safer sources, reducing demand in affected areas and consequently leading to lower prices. This suggests that strategic developments in the supplier's LGA primarily affect production, driving up prices. However, for yellow maize, looting and arrests in the trader's LGA could push a drop in demand, prompting suppliers to lower their prices to attract other buyers. Since strategic development events include looting and arrests, buyers would be unwilling to go to these areas, which in turn drives prices down

Third, violence shocks generally have a greater relationship with prices when occurring in the trader's own LGA rather than the supplier's LGA, though the effect varies by violence type and maize variety. Armed confrontations and explosion events are significantly and positively related to prices in the trader's own LGA but are not significant in the supplier's LGA. As many traders live in their own LGA, they are more exposed to local violence. However, violence against civilians has a larger negative effect on prices at the supplier's LGAs for each maize type (N365.74 vs. N475.86 for white maize and N135.43 vs. N766.51 for yellow maize). This supports our hypothesis that, in the supplier's LGA, violence can suppress demand to the extent that prices decline, as traders may avoid traveling to these areas due to safety concerns.

Table 3.6: Results of the Correlated Random Effects model on Price of Maize (White and Yellow)

Dep Var: Price Maize Naira/100kg: White and Yellow	Price White Maize	Price Yellow Maize
Own LGA		
Presence NSAA traders LGA-Same season (base 0)	300.16 (418.089)	436.81** (203.155)
Presence NSAA traders LGA-previous season (base 0)	-1,363.10 (2,347.891)	-2,464.38 (1,635.398)
Number of years of NSAA presence traders LGA	-186.61* (142.188)	-122.20*** (41.213)
Number of armed confrontations own LGA	334.32*** (38.564)	630.56*** (169.143)
Number of explosions own LGA	-447.52 (288.276)	143.41*** (29.781)
Number of violence against civilians own LGA	-365.74*** (45.504)	-135.43*** (4.055)
Strategic development own LGA (base 0)	7,001.68*** (1,257.973)	-222.69 (5,496.489)
Violence Index traders LGA- Previous Season	-4,788.60*** (1,360.394)	3,539.99** (1,691.671)
Urban density traders LGA	-0.05 (0.180)	-0.21** (0.105)
Violence Index *Urban density (trader's LGA)	0.55*** (0.207)	-0.42 (0.688)
Main supplier's LGA		
Presence NSAA main suppliers' LGA- Same season (base 0)	-384.30 (949.156)	-217.08 (132.305)
Presence NSAA main suppliers' LGA- previous season (base 0)	894.53 (1,337.492)	1,125.77* (599.977)
Number of years of NSAA presence main suppliers' LGA	-96.91 (157.790)	-59.22 (117.488)
Number of armed confrontation main suppliers' LGA	17.62 (235.849)	-25.96 (197.452)
Number of explosions main suppliers' LGA	297.87 (201.078)	166.16 (220.166)
Number of violence against civilians main suppliers' LGA	-475.86*** (81.303)	-766.51*** (212.107)

Table 3.6 (cont'd)

	Price White Maize	Price Yellow Maize
Dep Var: Price Maize Naira/100kg: White and Yellow		
Strategic development main suppliers' LGA (base 0)	1,520.03 (2,784.358)	-2,601.47*** (262.534)
Violence Index main suppliers' LGA- previous season	-224.28 (1,028.141)	1,541.96 (1,126.893)
Urban density main suppliers' LGA	0.43* (0.225)	0.05 (0.209)
Violence Index *Urban density (supplier's LGA)	0.20** (0.082)	0.19*** (0.058)
Other territorial and trader characteristics		
Mean daily temperature 2020 trader's LGA	565.96 (421.780)	675.29** (319.073)
Mean daily rainfall (mm) 2020 trader's LGA	4,451.85** (1,808.483)	3,588.63 (2,432.667)
Mean daily temperature 2020 supplier's LGA	-508.52 (1,083.362)	-493.55*** (154.716)
Mean daily rainfall (mm) 2020 supplier's LGA	-1,761.02 (1,788.988)	2,585.15** (1,090.798)
Trader's LGA is located in a State Capital	1,451.43 (2,288.110)	2,492.36 (2,832.248)
Suppliers' LGA is located in a State Capital	1,483.43 (1,321.673)	2,557.73*** (599.358)
Distance to main supplier (km)	2.39 (3.276)	0.61 (8.665)
Distance to major city (km)	14.12*** (0.970)	25.22*** (3.325)
Distance supplier to capital (km)	7.19 (27.216)	-4.22 (14.683)
Literacy rate at own LGA	-90.04** (44.424)	-96.87*** (8.863)
Literacy rate at supplier's LGA	-46.11 (203.197)	-23.59 (111.780)
Supplier type (base farmers)		
Farmer groups/associations/cooperatives	-869.70 (1,990.528)	-1,770.41 (1,302.604)
Rural traders	-353.40 (374.371)	624.64 (534.405)
Other urban wholesalers	723.83 (1,656.945)	502.69 (2,923.482)

Table 3.6 (cont'd)

Dep Var: Price Maize Naira/100kg: White and Yellow	Price White Maize	Price Yellow Maize
Brokers	-1,392.44* (748.952)	-2,603.07*** (601.762)
Trader Picked up maize (base 0)	-1,140.70 (803.207)	8.51 (351.373)
Part of an association (base 0)	-1,908.60*** (266.241)	-2,165.89*** (289.740)
Number of stalls	977.92*** (185.980)	2,470.35* (1,314.573)
Size (base small)	584.28*** (137.348)	-237.42** (103.323)
Sex (base male)	725.30*** (165.196)	-353.28 (845.757)
Location (base rural)	3,740.04 (2,434.845)	4,040.32 (2,528.422)
Education (base none)		
Primary	53.24 (35.843)	-809.17*** (53.995)
Secondary	311.24* (187.014)	-1,089.39*** (164.283)
University	-1,961.67*** (379.721)	-1,744.97 (1,411.787)
Koranic school	-1,003.81*** (55.576)	-2,079.47*** (357.199)
Other	1,640.76*** (288.147)	4,231.50* (2,507.094)
Experience	-59.50 (37.437)	-15.01 (20.120)
Age (year)	38.15 (31.274)	29.96** (12.316)
Islamic (base: Christian)	59.63 (86.620)	220.37* (115.350)
Region of trader (Base North)	914.87 (2,339.623)	1,127.07 (5,534.295)
Region of Supplier (Base North)	-1,273.76 (1,190.531)	109.31 (2,992.461)
Produces maize (Base no)	-892.35*** (266.285)	-1,813.02** (841.344)
Season (base: low)	-5,355.07*** (77.757)	-5,782.08*** (232.697)

Table 3.6 (cont'd)

Dep Var: Price Maize Naira/100kg: White and Yellow	Price White Maize	Price Yellow Maize
Constant	-2,938.29 (11,047.057)	22,684.12 (19,640.273)
Observations	1,006	652

Robust standard errors in parentheses

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

We also find higher sensitivity of yellow maize prices compared to white maize associated with violence in the suppliers' LGA but not consistent in the direction of effects. More specifically, higher levels of violence against civilians and lootings are associated with lower yellow maize prices (compared to regions with lower levels of such violent acts) while the presence of NSAA actors in the previous season is associated with higher prices while the effects are insignificant for white maize. These observations could be attributed to several factors, one of which is the differential trading patterns between the two maize types. As indicated, a larger number of traders are involved in the trade of white maize, making it more readily available in the market. If there are fewer sourcing options for white maize, however, prices might not react as much to violent acts at sourcing locations but could be more likely to increase when shocks occur at the traders' base. Moreover, the distinct end-uses of yellow and white maize further contribute to this disparity. Yellow maize, often utilized as feed for cattle, may face disruptions in transportation and distribution channels, leading to heightened price sensitivity. In contrast, white maize, primarily intended for human consumption, may benefit from a more resilient supply chain during periods of violence.

A fourth, is that there is evidence of some adaptation to violence among traders. In the case of the trader's own LGA, we find that traders located in LGAs with longer exposure to

violence observe lower prices in both types of maize compared to those who don't have this exposure. An increase of one year in the presence of NSAA at the trader's LGA level is associated with a reduction in prices for yellow maize by N122.20 and of N186.61 for white maize, statistically significant at the 1% and 10% level, respectively. These results suggest that heightened presence of NSAA prompts community members to internalize associated risks, consequently modifying their behaviors accordingly.

Five, there is a positive significant interaction association between violence and urban density for all types of maize and at the supplier's LGAs and for white maize in the traders' own LGA. Our findings resonate with George et al. (2020) and Van Den Hoek (2017), particularly in the Nigerian context, where the impact of violence on prices is pronounced in urbanized areas. Given the strategic targeting of markets by groups such as Boko Haram, urban centers become focal points for conflict events. Consequently, the disruptive effects of violence on agricultural production and market activities are heightened in these densely populated areas.

These results also coincide with Steinhübel and Minten (2023) paper that demonstrated that the impact of conflict on agricultural development varies depending on the geographical context. We differ in our findings as our results show that the effect of violence on price is bigger on larger urban centers, whereas their paper finds that, in general more remote areas price shocks caused by violence were higher. However, our study diverges from their methods in that we incorporated institutional variables, particularly the literacy rate, which emerged as highly significant at the trader's own location. This discrepancy suggests a nuanced interplay between urbanization, poverty, and violence. It's plausible that urbanization and poverty may counteract each other's effects in some cases. Alternatively, it could indicate that the influence of

urbanization on violence is less direct, and instead, other factors such as resource distribution within urban spaces might be more pivotal in shaping market dynamics and prices. The increase sensitivity of urban markets to violent shocks may also be attributed to the greater economic vulnerability of densely populated regions, where disruptions can have more significant and immediate consequences on supply chains and market dynamics. Unlike rural communities, urban populations may face challenges in smoothing their consumption patterns through reliance on local production, making them more susceptible to the disruptive effects of violence on food prices.

Sixth, from our results we can see that lagged violence shocks have a significant relationship with the price traders pay in their own LGA, but the effect of these variables differs between white maize (where there is a negative effect on prices) and yellow maize (where there is a positive effect). These results indicate that lagged violence shocks affect input prices for traders differently depending on the type of maize, revealing how traders internalize these costs. The negative effect related to white maize input prices (N4,788.60) suggests that past violence may lead to reduced demand or trader are able to find mitigating strategies to reduce prices in the future. This aligns with the role of white maize as a staple food, where demand might be more sensitive to violence-induced disruptions, encouraging traders to internalize shocks by lowering input costs. Conversely, the positive effect on yellow maize input prices (N3,539.99) implies that violence shocks drive up costs, possibly due to sustained demand for yellow maize as animal feed, where traders have fewer alternatives.

Seven, there is a positive association between maize price and the distance to major cities (in kilometers) for traders' Local Government Areas (LGAs). One extra kilometer from the trader's

location to a capital city is related with increases of the price of white maize by N14.12 and the price of yellow maize by N25.55 at the 1% level. This finding suggests that traders located closer to major urban centers are better positioned in bargaining for favorable prices. Improved market access, stemming from proximity to urban hubs, empowers these traders to negotiate more advantageous deals with suppliers. The shorter distance allows for easier exploration of a broader range of suppliers, fostering a more competitive landscape.

Eight, producing maize and being part of an association is significantly related to lower maize prices. Traders who grow maize themselves typically pay an average of N892.35 less per 100kg of white maize and N1,813.02 less per 100kg of yellow maize compared to those who do not. Similarly, traders who are part of an association pay about N1,908.60 and N2,165.89 less per 100kg of white and yellow maize, respectively, than those who aren't members. These cost reductions are likely due to the stronger bargaining power that comes from both association membership and self-production. Association members can negotiate prices more effectively as a collective, while traders who produce their own maize are less dependent on external suppliers, giving them more leverage in setting prices. These findings highlight how maize production and association membership can serve as effective ways to buffer against the price impacts of violence.

IX. ROBUSTNESS CHECKS

To ensure the robustness of our findings, we consider two alternative specifications of our empirical model. First, we investigated whether employing an alternative violence measure would yield consistent results. Following the methodology of George et al. (2020), we opted to utilize fatalities as our violence metric. In this iteration of the model (the CRE), we substituted

the violence variables with fatalities at both the trader and supplier LGAs. Again, we included the lagged effect of fatalities on prices while retaining the same measures of violence exposure (NSAA presence and number of years).

Secondly, we performed a statistical robustness check by employing a pooled Ordinary Least Squares (OLS) approach rather than the CRE. This analysis allowed us to evaluate the stability of our results while assuming no trader specific effects, providing further insights into the relationship between violence and maize prices.

The results of these robustness checks are in tables 3.6 and 3.7. Looking at the results, a few points emerge:

From the first robustness check, our analysis revealed that the violence event variables yielded more significant results compared to fatalities. This result suggests that violence encompasses various forms need to be included when studying violence. Therefore, the comprehensive nature of multiple violence variables provides a more robust framework for understanding its impact on maize prices.

Second, when individual heterogeneity is not taken into account, exposure to shocks gain more significance, and the signs of the effect of violence shocks change. This suggests that without controlling for individual differences, the relationship between violence and maize prices may be misrepresented. Accounting for individual heterogeneity allows us to capture the direct impact of violence more accurately, confirming that it is a strong determinant of maize prices for traders in Nigeria. This approach also controls for unobservable, internalized actions that traders might take to mitigate the effects of violence shocks, helping us distinguish these adaptive behaviors from the actual exposure to violence.

In addition, the significance of the distance between the trader's own LGA and major cities remains consistent across all analyses, reaffirming its importance in shaping market outcomes. Furthermore, engaging in maize production and association membership consistently correlate with lower maize prices, emphasizing the efficacy of these strategies in mitigating the impact of violence-induced shocks on market prices.

Table 3.7: Results of the Correlated Random Effects model on Price of Maize (White and Yellow) using fatalities

Dep Var: Price Maize Naira/100kg: White and Yellow	Price White Maize	Price Yellow Maize
Presence NSAA traders LGA-Same season (base 0)	1,244.06** (601.622)	1,451.83*** (55.078)
Presence NSAA traders LGA-previous season (base 0)	-1,015.29 (2,544.479)	-1,498.94 (1,353.332)
Number of years of NSAA presence traders LGA	60.27 (48.764)	-244.04 (153.097)
Fatalities at traders LGA-same season	-6.13 (17.071)	32.69* (18.994)
Fatalities at traders LGA- Previous Season	8.48 (23.043)	110.37** (47.164)
Urban density traders LGA	-0.17*** (0.057)	-0.16 (0.159)
Fatalities *Urban density (trader's LGA)	0.00* (0.002)	0.01** (0.004)
Presence NSAA main suppliers' LGA- Same season (base 0)	-1,106.04* (646.249)	-1,175.12*** (134.546)
Presence NSAA main suppliers' LGA- previous season (base 0)	614.41 (610.205)	548.58 (383.764)
Number of years of NSAA presence main suppliers' LGA	-106.91 (208.475)	-100.47 (114.632)
Fatalities at main suppliers' LGA- Same season	11.01 (19.219)	1.56 (22.515)

Table 3.7 (cont'd)

	Price White Maize	Price Yellow Maize
Dep Var: Price Maize Naira/100kg: White and Yellow		
Fatalities at main suppliers' LGA- previous season	-9.82 (21.599)	-14.38 (20.003)
Urban density main suppliers' LGA	0.35* (0.202)	0.01 (0.120)
Fatalities *Urban density (supplier's LGA)	0.00 (0.002)	-0.00 (0.002)
Mean daily temperature 2020 trader's LGA	-516.35*** (191.786)	-297.02 (326.327)
Mean daily rainfall (mm) 2020 trader's LGA	971.38 (1,114.873)	1,020.53 (1,993.728)
Mean daily temperature 2020 supplier's LGA	-367.57 (1,097.710)	-610.38* (360.775)
Mean daily rainfall (mm) 2020 supplier's LGA	-2,197.81 (2,188.284)	1,191.61 (1,749.885)
Trader's LGA is located in a State Capital	4,807.19*** (318.309)	4,088.96*** (1,322.100)
Suppliers' LGA is located in a State Capital	1,790.89*** (579.198)	2,459.39*** (29.785)
Distance to main supplier (km)	3.66 (4.848)	2.63 (9.870)
Distance to major city (km)	28.80** (11.361)	31.61*** (8.529)
Distance supplier to capital (km)	13.22 (32.796)	3.57 (20.156)
Literacy rate at own LGA	-9.46 (7.219)	-41.78*** (14.284)
Literacy rate at supplier's LGA	-34.25 (212.623)	-10.63 (131.748)
Supplier type (base farmers)		
Farmer groups/associations/cooperatives	-358.01 (1,418.944)	-674.66 (588.968)
Rural traders	-473.14 (558.311)	480.56 (729.461)
Other urban wholesalers	2,342.09*** (558.552)	1,308.97 (2,322.842)
Brokers	-1,958.95* (1,164.589)	-3,189.16*** (252.837)
Trader Picked up maize (base 0)	-894.63 (639.686)	377.67 (865.573)
Part of an association (base 0)	-2,083.49*** (434.111)	-2,436.87*** (652.710)

Table 3.7 (cont'd)

Dep Var: Price Maize Naira/100kg: White and Yellow	Price White Maize	Price Yellow Maize
Number of stalls	1,023.47*** (135.554)	2,638.06** (1,325.758)
Sex (base male)	121.72 (235.401)	-623.72*** (212.662)
Size (base small)	174.26 (133.916)	-547.51 (827.745)
Location (base rural)	3,008.84** (1,252.783)	2,920.50** (1,385.333)
Education (base none)		
Primary	-314.37*** (38.432)	-1,103.77*** (153.494)
Secondary	-9.01 (207.334)	-1,403.44*** (98.593)
University	-1,854.99*** (431.253)	-2,078.35 (1,334.298)
Koranic school	-1,269.35*** (92.611)	-2,087.98*** (327.266)
Other	1,020.62* (569.869)	3,620.86 (2,462.334)
Experience	-33.22 (47.881)	-1.80 (24.310)
Age (year)	19.94 (36.686)	12.36 (14.584)
Islamic (base: Christian)	45.27* (25.631)	78.12 (106.718)
Region of trader (Base North)	-1,715.32 (2,733.771)	-877.96 (5,810.789)
Region of Supplier (Base North)	470.76 (942.299)	2,013.52 (4,458.005)
Produces maize (Base no)	-1,118.65** (530.554)	-1,811.66** (809.644)
Season (base: low)	-5,865.82*** (12.002)	-6,737.68*** (105.889)
Constant	21,581.75*** (1,577.674)	46,566.39*** (8,007.420)
Observations	1,006	652

Robust standard errors in parentheses

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

Table 3.8: Results of the Pooled OLS model on Price of Maize (White and Yellow)

Dep Var: Price Maize Naira/100kg: White and Yellow	Price White Maize	Price Yellow Maize
Presence NSAA traders LGA-Same season (base 0)	-387.38 (810.092)	-754.39 (1,031.579)
Presence NSAA traders LGA-previous season (base 0)	-1,196.53 (1,069.994)	-1,980.30* (1,188.272)
Number of years of NSAA presence traders LGA	-206.32** (93.949)	-251.03** (118.844)
Number of Armed confrontations own LGA	-113.00 (234.809)	694.27* (381.432)
Number of explosions own LGA	-514.44*** (146.133)	-562.61** (257.823)
Number of violence against civilians own LGA	497.42*** (156.264)	9.60 (220.717)
Strategic development own LGA (base 0)	1,673.12 (1,651.032)	6,877.27*** (1,948.867)
Violence Index traders LGA- Previous Season	390.13 (785.285)	707.01 (1,012.548)
Urban density traders LGA	-0.05 (0.096)	-0.13 (0.093)
Violence Index *Urban density (trader's LGA)	0.52*** (0.147)	0.32 (0.216)
Presence NSAA main suppliers' LGA- Same season (base 0)	-2,026.49*** (724.111)	-1,973.71*** (668.970)
Presence NSAA main suppliers' LGA- previous season (base 0)	253.32 (566.418)	257.33 (768.262)
Number of years of NSAA presence main suppliers' LGA	9.90 (90.628)	89.39 (105.616)
Number of Armed confrontation main suppliers' LGA	-113.00 (234.809)	694.27* (381.432)
Number of explosions main suppliers' LGA	-514.44*** (146.133)	-562.61** (257.823)
Number of violence against civilians main suppliers' LGA	497.42*** (156.264)	9.60 (220.717)
Strategic development main suppliers' LGA (base 0)	1,673.12 (1,651.032)	6,877.27*** (1,948.867)
Violence Index main suppliers' LGA- previous season	390.13 (785.285)	707.01 (1,012.548)
Urban density main suppliers' LGA	0.23 (0.198)	-0.06 (0.259)

Table 3.8 (cont'd)

Dep Var: Price Maize Naira/100kg: White and Yellow	Price White Maize	Price Yellow Maize
Violence Index *Urban density (supplier's LGA)	0.01 (0.141)	0.09 (0.190)
Mean daily temperature 2020 trader's LGA	194.51 (274.824)	138.25 (342.874)
Mean daily rainfall (mm) 2020 trader's LGA	3,118.84** (1,366.217)	2,377.99 (1,660.642)
Mean daily temperature 2020 supplier's LGA	-157.40 (222.679)	-625.99** (307.216)
Mean daily rainfall (mm) 2020 supplier's LGA	182.67 (1,180.559)	1,390.67 (1,284.891)
Trader's LGA is located in a State Capital	2,504.99 (1,731.356)	3,288.69* (1,802.427)
Suppliers' LGA is located in a State Capital	-2,132.13 (2,373.153)	-1,528.81 (2,331.438)
Distance to main supplier (km)	2.60 (1.638)	4.79** (2.336)
Distance to major city (km)	19.62** (8.975)	27.65*** (9.757)
Distance supplier to capital (km)	3.41 (3.447)	4.25 (4.610)
Literacy rate at own LGA	-58.23** (25.785)	-74.14** (33.885)
Literacy rate at supplier's LGA	9.25 (19.705)	21.76 (39.168)
Supplier type (base farmers)		
Farmer groups/associations/cooperatives	34.94 (1,020.305)	-756.39 (1,815.323)
Rural traders	148.85 (425.806)	1,747.32*** (647.207)
Other urban wholesalers	2,073.07 (2,027.071)	2,656.36 (2,376.751)
Brokers	551.14 (436.201)	1,143.24 (924.390)
Trader Picked up maize (base 0)	-662.27 (531.141)	-827.64 (595.097)
Part of an association (base 0)	-2,096.16*** (380.427)	-2,325.92*** (576.103)
Number of stalls	1,049.18*** (357.241)	2,531.92*** (730.611)

Table 3.8 (cont'd)

Dep Var: Price Maize Naira/100kg: White and Yellow	Price White Maize	Price Yellow Maize
Size (base small)	211.03 (336.765)	-487.62 (453.752)
Sex (base male)	198.61 (440.769)	-501.82 (686.181)
Location (base rural)	3,931.01*** (1,007.206)	3,700.76** (1,540.516)
Education (base none)		
Primary	-226.04 (837.546)	-1,330.43 (975.721)
Secondary	185.69 (814.096)	-1,431.32 (1,032.015)
University	-2,129.59 (1,492.060)	-2,174.49 (1,413.359)
Koranic school	-1,080.89 (754.269)	-2,141.95* (1,101.670)
Other	1,305.54 (1,241.442)	3,633.63 (3,100.271)
Experience	-31.65 (36.433)	0.58 (39.759)
Age (year)	-43.11 (36.712)	-5.96 (41.001)
Islamic (base: Christian)	22.86 (23.075)	17.71 (32.460)
Region of trader (Base North)	-151.59 (568.422)	95.30 (539.756)
Region of Supplier (Base North)	-657.87 (2,281.074)	75.99 (2,780.235)
Produces maize (Base no)	-950.90 (1,358.240)	1,802.59 (1,726.985)
Season (base: low)	-1,201.53*** (400.677)	-1,958.50** (896.814)
Constant	-5,774.59*** (336.552)	-5,761.24*** (619.759)
Observations	1,006	652

Robust standard errors in parentheses

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

X. CONCLUSIONS

Overall, our paper's main objective was to try to respond to the question: does violent conflict have an effect price paid by maize traders? To do so, we estimated the effect of violent events and presence of non-state armed actors (NSAA) on Maize traders in Nigeria, using a survey collected in 2022. We varied our estimation though different seasons and types of maize. Overall, we found the following:

Our analysis reveals a strong, statistically significant impact of violence on maize procurement prices for Nigerian traders, with effects varying between the trader's own LGA and that of suppliers. armed confrontations and explosions drive up prices for both white and yellow maize, as these disruptions to production resources push up input costs, highlighting the added transaction costs of violence—limiting trader mobility and sometimes even resulting in market closures. In contrast, violence against civilians has a significant negative effect on prices, likely due to diminished demand, as buyers are discouraged from frequenting areas where these events occur. This drop in demand is particularly noticeable in the supplier's LGA, which supports our hypothesis that safety concerns limit market engagement.

Beyond violent shocks, the findings also suggest that exposure to prolonged violence and experiencing a violent shock in previous seasons has a distinct impact on price dynamics, one that differs by maize type. Traders in areas with long-term exposure to violence demonstrate an ability to internalize these risks, finding ways to mitigate costs and adapt over time. For instance, an increase in the number of years of NSAA presence in the traders own LGA, or presence of a NSAA in the previous season was associated with lower prices for yellow maize. As well, a higher level of violence on the previous season also reduced the price of white maize. This is most likely

explained as traders develop coping mechanisms that allow them to negotiate more effectively or source alternatives locally. In contrast the presence of NSAA within the same season and experiencing higher violence in the previous season showed a positive relationship with yellow maize prices, indicating that even with adaptive strategies, some input costs remain elevated, especially given yellow maize's role as animal feed and its less flexible supply chain.

Three, the positive interaction effect between violence and urban density is significant across all maize types and LGA locations, underscoring the pronounced impact of violence on prices in urbanized areas. This finding aligns with prior research, emphasizing the heightened vulnerability of densely populated regions to market disruptions induced by violence. Urban centers, serving as focal points for conflict events, experience amplified effects on agricultural production and market activities.

Lastly, the study identifies important mechanisms through which traders can mitigate the effects of violence. Traders who engage in maize production and are part of an association significantly obtain lower maize prices. These findings suggest that diversifying ones maize source (e.g. by participating in agriculture) and social networks (membership in associations) provides traders with advantageous bargaining positions, contributing to lower maize procurement prices. These strategies are essential buffers against violence-driven price volatility, highlighting the role of institutional and individual resilience in conflict-prone settings. As well these results can help identify policy tools to help traders prevent violence related price shocks through these mitigating activities.

This paper shows the critical importance of examining the impact of violence not only in the residential locations of individuals, firms, and actors but also in the areas where they conduct

their business transactions. This distinction becomes particularly important for informing public policy, especially in efforts aimed at assisting victims and mitigating the shocks of violence. By recognizing that the effects of violence extend beyond immediate residences to encompass business environments, policymakers can tailor interventions to address the diverse ways in which violence disrupts economic activities.

Moreover, this research also pushes back against the idea that violence always has straightforward, negative impacts. While shocks often drive prices up, our findings show a more complex picture where actors in violent areas develop effective ways to offset these impacts. This new perspective calls for a deeper look into how violence, economic activity, and market dynamics interact. Recognizing the adaptive strategies that individuals and businesses use can help us understand the nature of these challenges and suggests that resilience policies need to be tailored to the specific context for real effectiveness.

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