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Confluence of climate, violence, disease, and cost shocks: vulnerability of and impacts on Nigerian Maize Traders

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Confluence of climate, violence, disease, and cost shocks: vulnerability of and impacts on Nigerian Maize Traders

Abstract: Using unique primary survey data on 1100 Nigerian maize traders, we use probit models to estimate the probability of experiencing exogenous shocks and its relationship to trader characteristics (gender, size, and location), and traders vulnerability, measured as the probability of experiencing severe impacts. We study five types of exogenous shocks: climate, violence, price changes, spoilage, and COVID-19. We analyze the relationship among these shocks and the trader characteristics that make traders more vulnerable. We find traders are prone to experience more than one shock, which increases the intensity of the shocks. This is especially the case for price shocks, which are often accompanied by violence, climate, and COVID shocks. The poorer Northern region is disproportionately affected by shocks, with Northern traders experiencing more price shocks, and Southern traders more violence shocks but in their long supply chains from the North. Women are more prone to experience a violence shock and men, a severe climate event. A limitation is that the data only analyze the general degree of impact of a shock rather than quantify lost income. A key policy implication is the need for a differentiated response and prevention strategy based on the particular mix of shocks and types of traders and regions.

1. Introduction

The food system of Nigeria has been pummeled over the past two decades by a series of shocks (bird flu, energy crisis, the 2007/8 international food crisis), all bringing surges of costs and uncertainty. These were layered on a long history of climate variation and uncertainty, droughts in the North, and floods in the South. Recently Nigeria's food system has been subjected to a new confluence of shocks – intensified climate variation and shocks, COVID-19, a surge in banditry on the roads, civil conflict with the rise of Boko Haram, and fuel, fertilizer, and grain price surges due to the Russian invasion of Ukraine and other domestic and international factors.

There is much discussion of the effects of these shocks on the farm sector. But these shocks can also hurt the post-farmgate segments of the food supply chain (FSC) such as maize traders which are the focus of our analysis. The post-farmgate segments, one being traders, are important in Nigeria for several reasons. First, there is substantial rural and urban employment in food processing, wholesaling (trading), retailing, and logistics. Second, the FSC is essential for food security because in Nigeria 95%, of urban food consumption is purchased (in comparison to subsistence farming) and 78% of rural food consumption is purchased (with only 22% of rural food coming from "subsistence farming"). Thus 88% of all food consumed in Nigeria is purchased and comes from FSCs, short, medium length, or long. Fourth, the rural-urban FSC is important in Nigeria because 58% of all food consumed is consumed in urban areas (which constitute 50% of the national population). However, rural-rural and urban-rural FSCs are also important as most food consumed in rural areas is purchased (as noted above. Finally, domestic FSCs are far more important than imports in Nigerian food security. Less than 10% of food consumed is imported (in ton terms); More than 90% comes from domestic FSC carrying domestic products (Liverpool-Tasie et al., 2021).

Moreover, though there is extensive literature on the vulnerability of agrifood actors to exogenous shocks (such as climate, violence, or spoilage), most research has focused on individual shocks, and failed to describe the convergence of these stressors. This approach has drawbacks. First, focusing on one shock can lead to underestimation or overestimation of its effect, as vulnerability can depend on the interactions of many shocks working together. Second, failing to understand the clustering or confluence of shocks can lead to inadequate mitigating strategies. Adaptative measures focused on mitigating one shock might be counterproductive or even exacerbate the effects of a different shock (Feola et al., 2015). For example, investing in machinery that can reduce the effects of temperature variations caused by climate change could increase the probability of being a target to banditry as it can signal higher wealth.

Here we examine the incidence of shocks on and vulnerability of maize traders in Nigeria. We study five types of shocks: climate, violence, price changes, spoilage, and COVID-19. We focus on understanding the relationship among these shocks (that is, do they cluster or affect the trader as a "confluence") and the trader characteristics that make them more vulnerable.

We address three questions. First, are female, rural, and Northern (poorer region) traders more vulnerable to exogenous shocks than male, urban, and Southern traders? Second, are the more vulnerable traders more prone to experience more than one shock? Third, does experiencing different shocks increase the intensity of the impacts of the shocks themselves (did traders classify the shock as having a big negative impact)? Answering these questions will help understand the nature of these shocks and if there is an uneven and unequal distribution of negative impacts. As well, better understanding trader vulnerability can lead to better tactics that can reduce such exposure or alleviate these challenges, enabling value chains to function with greater efficiency.

To address these questions we included a module on shocks in a comprehensive, detailed primary survey of 1100 traders in November 2021. The traders are based in urban wholesale markets and regional wholesale markets in main production regions. This is among the largest surveys of food traders in Africa. We asked the traders about their assets, purchasing, marketing, and value-added behaviors. The shocks module asked if the traders had experienced the following shocks in the previous year: (1) direct shocks from climate factors – transit road washouts, and floods and droughts in farm areas; (2) maize price surges and maize spoilage (that may arise at least partially from climate factors like drought and heat and humidity); (3) energy cost surges; (4) conflict and banditry; (5) shocks from COVID-19 and policies linked to containing it, such as lockdowns. We also asked about traders' strategies to avoid or cope with these shocks.

The paper proceeds as follows. The first section provides a literature review on the incidence and confluence of shocks. The second section discusses the data used; the third section presents a conceptual framework; the fourth section the econometrics model and application approach; the fifth section descriptive statistics; the sixth section, regression estimation results, and the last section, conclusions.

2. Literature review

There is an emerging literature examining the effects of individual shocks pertaining to climate, violence, price changes, spoilage and COVID-19 on FSCs. Climate change has disrupted the stability and predictability of food production, leading to lower crop yields, higher production costs, and reduced quality. This can have ripple effects throughout the entire value chain, leading to food insecurity, reduced incomes for farmers, and higher prices for consumers (Sartori et al., 2021).

Studies have shown how violence in rural areas, including conflicts over land and resources, can disrupt FSCs by impeding the movement of goods and people, damaging infrastructure, and reducing investment (FAO, 2020). Price changes, whether due to market fluctuations or policy interventions, can have significant impacts on food producers, processors, and retailers, affecting their profit margins and ultimately, their ability to sustain their businesses (Deaton, 2020). Spoilage has been a major challenge facing agri-food value chains, particularly in developing countries where inadequate infrastructure and poor storage facilities can lead to high levels of post-harvest losses (FAO, 2019). Studies have shown how COVID-19 disrupted the FSCs both along the chains and in farm and consumer segments (UNEP, 2021).

However, few studies have examined FSC actors' experience of and vulnerability to clusters or confluences of shocks. Within the climate literature, economists have integrated precipitation data as exogenous sources of shocks into various empirical models, aiming to gauge the retrospective ramifications of weather conditions (Dell, Jones, & Olken, 2014). This approach has been used to study the influence of weather shocks on household consumption in Ethiopian villages, (Dercon, 2004; Dercon and Krishnan, 2000; and Porter 2012). There are also studies that quantify the welfare effects of drought and price inflation in Ethiopia (Hill and Porter, 2017).

Several studies have also examined how climate change and urbanization have spurred violent conflict (Baechler 1999, Homer-Dixon 1994). Burke et al. (2009) estimate that an increase of one degree Celsius will increase the likelihood of internal armed conflicts in sub-Saharan African countries by 4.5%. Increased droughts and desertification have increased the migration of nomadic herders into new farmer territories, increasing farmer-herder conflicts (Nnaji et al., 2022)

More recently studies have addressed "multiple stressors" that actors within the AFC face (Feola et al., 2015; Guido et al., 2020; Haq, 2015; Hicks, 2021; McDowell and Hess, 2012). These have mostly been qualitative studies of multiple shocks such as climate change and violence affecting farmers. This perspective has not been applied to off-farm segments of the AFC such as traders. We address that gap by examining multiple stressors of traders.

Data

We use a cross-section data set of maize traders collected in 2021 and some data from a first survey on the same sample in 2017. We surveyed 1195 maize traders in Northern and Southern Nigeria in 2017. We did the sampling based on our own census of maize traders in 63 main urban maize wholesale markets in Ibadan in the South and in Jos, Kaduna, Kano, and Katsina in the North (Liverpool-Tasie et al. 2017).

We resurveyed 1111 traders in November 2021 to get a (near) panel. Table 1 shows their characteristics. Nearly 90% are male and 93% are in based in the North (where the great majority of maize production is). Below we show however that many traders in both sets move maize from the North to the South and around the states of the North.

Table 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

The 2021 sample has 84 fewer traders than the 2017 sample because 84 (7%) of the 2017 sample stopped trading maize. Table 2 shows the reasons they dropped out: 51% dropped just to do more profitable business; 35% said they dropped because they could not secure funds to continue trading; 10% dropped because of insecurity (Boko Haram, robbers, banditry); 5% dropped because of death or fire; but none dropped due to COVID factors (disease or lockdown). 40% left before 2020 and 60% in 2020 or 2021. Thus, the timing of most dropping happened to be at the same time as COVID (and a surge in insecurity). It is possible that there is a correlation between being unable to secure funds or wanting to move to a more profitable business and COVID-related challenges.

Table 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

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; https://data.chc.ucsb.edu/products/CHIRPS-2.0/).

3. Conceptual Framework

The concept of vulnerability that we are using has two dimensions: exposure and sensitivity. Exposure refers to the hazards that threaten traders and sensitivity denotes how much a shock affects a trader (Guido et al., 2020). To econometrically explain vulnerability of traders to exogenous shocks we use two measurements of incidence as dependent variables. First, we focus on exposure - the probability of experiencing an exogenous shock independent of its severity. Secondly, we focus on impact - the probability of experiencing 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 and location of their trading activities in space (hence size and urban location) and their general vulnerability (size 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 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.

Table 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

Our hypotheses concerning the relationship between trader characteristics and shocks vary with the type of shock and its severity. We posit that larger traders will be more exposed to violence than smaller traders because larger traders might be perceived as wealthier and therefore a better target for banditry.. We also hypothesize that larger traders 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 seems 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 further along 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, climate, COVID19 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 change due to preexisting gender inequalities where they have less access to mitigating tools such as credit and education.

By contrast, it seems more 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).

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 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 more together which lead to traders' facing sets of them that can in confluence cause more harm. Some shocks that are complementary (climate shocks and spoilage) which enforce this confluence.

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 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, we must take into account that 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. There are correlations between a region and certain shocks as well. For example northern Nigeria has had more desertification, increasing the probability of climate related shocks and potentially spoilage shocks. To account for this, we include climate variables (such as temperature and rainfall) and violence variables (number of years of the presence of an armed group) in each LGA (a local county is called a "local government area", LGA, in Nigeria). These variables can serve as indicators of places that have poorer resources due to harsher weather conditions and more presence of general violence conflict.

A second source of non-randomness can come from the fact that traders can change their own actions to reduce their exposure and sensitivity to shocks. Traders can choose were they sell their goods (North or South) and their size. Overall, 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 directly the knowledge and awareness of a trader, we do have a proxy that is useful: if the trader had experienced each shock in 2017 (except COVID). Due to the presence of this non-randomness we cannot claim causality but only correlations or associations.

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

4. Regression model and estimation method

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

$$g_i = \boldsymbol{M_i}\beta_M + \boldsymbol{MV_i}\beta_{MV} + \boldsymbol{X_i}\beta_x + u_i$$

Where g_i is a binary indicator of violence 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. β_m, β_{MV}, $\beta_{x,}$ are the coefficient estimates associated with the study covariates. u_{it} is the error term which we assume is distributed $u_i| \quad M_{it}, MV_i, X_i,$ ~ N(0,1).

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

$$\Pr\,(g_{it} = 1|M_{it}, MV_i, X_{it},\ ) = \Phi(\boldsymbol{M_{it}}\beta_M + \boldsymbol{MV_i}\beta_{MV} + \boldsymbol{X_{it}}\beta_x) \qquad t = 1 \ldots T \qquad [2]$$

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.

5. Descriptive statistics

In the following we discuss the key findings shown in the descriptive Tables 4-11. Each Table shows the shares of traders having experienced a particular type of shock and the severity of these.

5.1. Climate/weather shocks

Table 4 shows that 14% of traders experienced a climate/weather shock. Table 5 shows that larger traders were a bit 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 6). These results together 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 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
Conditional on having this shock:				
% 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

Table 4 breaks down the types of climate shocks into droughts, floods, and road washouts. Floods were experienced by 4% of the traders (3% of North and 18% of South traders) as one would expect 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 wash-out (possibly because lack of culverts to divert flood flows); 11% of the North and 26% of South traders experienced these wash-outs. This could be due to climate differences between the regions but our survey did not show where the roads washed out. Given that the North depends on their own region (the North, where most maize is produced) and the South traders mainly source from the North, the climate shocks in the North transmit importantly to the South.

Table 4 also shows the severity of each climate shock. Of the traders that experienced a climate shock, 6% of traders went without an effect, 37% had only a small negative effect, 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. Complete recovery was a third for each of drought and washout but higher (46%) for floods.

Table 5. Shocks by size and region of the maize trader

	Size (share)		T-test
	Small	Large	T statistic
Share of wholesalers	42	58	
Shocks			
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	
Shocks			
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 6. Shocks by gender of the maize trader

	Sex (share)		T-test
	Male	Female	T statistic
Share of Wholesalers	88	12	
Shocks			
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

5.2. Conflict shocks

Table 7 shows that 48% of the traders experienced a conflict shock. The probability of the shock was 1.4 times higher for South-based traders than North-based traders: 47% of North traders versus 66% of South traders (Table 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 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
Conditional on having this shock:				
% 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 negative 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

Table 7 breaks down the types of conflict shocks into Boko Haram, farm-herder conflict, 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 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 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 county 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 importantly to the South.

Table 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 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 6 shows that female operators 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 majority of the female maize traders are found) and farmer-herder conflict rampant.

Table 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 shocks (for all shocks taken together). Complete recovery was 52% for Boko Haram shocks and 34% for herder-farm conflict and 24% for banditry. This highlights the significant challenge from banditry and herder-farmer conflicts often less discussed in international debates compared to Boko Haram.

5.3. Spoilage/loss/waste shocks

Table 8 shows that only 3% reported experiencing a spoilage/loss/waste shock. The probability of the spoilage shock was 3 times higher for North-based traders than South-based traders: 3% of North traders versus 1% of South traders (although Table 5 shows that these do not different statistically). 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 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
Conditional on having this shock:					
% 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

Table 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 5 shows spoilage shock exposure is thrice higher for large traders but the difference is not significantly statistically. Table 6 shows there is no difference in spoilage shocks between male and female traders.

5.4. Cost shocks

Table 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 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
Conditional on having this shock:			
% 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

Table 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 6 shows males are nearly twice as apt to experience a fuel price shock as females. This could 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 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.

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 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 5).

Table 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

5.5. Confluence of shocks

Table 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. This suggests that traders are more exposed to different sources of shocks and are not only vulnerable to one.

Table 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	
% 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

6. Regression Results

In Tables 12 and 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.

Table 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	0.46**	0.74***
		(0.104)	(0.189)	(0.208)
Number violence shocks	0.12*		0.11	0.36***
	(0.064)		(0.105)	(0.080)
Number of spoilage shocks	1.07***	-0.05		0.54
	(0.298)	(0.328)		(0.468)
Number of price shocks	0.32***	0.16**	-0.02	
	(0.066)	(0.068)	(0.123)	
Negative COVID effect (base =	-0.15	0.36***	0.17	0.89***

no negative effects)	(0.180)	(0.131)	(0.267)	(0.136)
Gender (base male)	-0.38	0.33	0.29	0.34
	(0.256)	(0.294)	(0.375)	(0.238)
Size (base small)	0.25	-0.10	-0.24	-0.05
	(0.180)	(0.132)	(0.289)	(0.145)
Region (base North)	-0.37	1.06**	-1.18	-0.89*
	(0.463)	(0.356)	(1.065)	(0.425)
General Shocks in 2017	0.09		0.39	
	(0.146)		(0.258)	
Violence Shock in 2017		0.13		
		(0.218)		
Price shock in 2017				-0.12
				(0.129)
Location (base rural)	-0.26	0.68***	0.40	0.43**
	(0.233)	(0.171)	(0.267)	(0.207)
Years violence presence	-0.04	0.09***	0.03	0.03
	(0.041)	(0.024)	(0.033)	(0.023)
Mean rainfall 2021	0.82**	-0.46*	-0.43	0.03
	(0.325)	(0.239)	(0.366)	(0.239)
Mean temperature 2021	0.34***	-0.05	-0.09	0.15**
	(0.095)	(0.076)	(0.127)	(0.076)
Age	0.00	-0.02**	-0.04**	-0.01
	(0.010)	(0.008)	(0.017)	(0.009)
Experience	-0.00	0.02	0.03**	0.01
	(0.010)	(0.010)	(0.013)	(0.010)
Islamic (base: Christian)	-0.54	0.27	1.12**	-0.78***
	(0.358)	(0.237)	(0.475)	(0.245)
Produces own maize (base 0)	-0.09	1.27***	0.52	-0.36**
	(0.258)	(0.177)	(0.349)	(0.174)
Trader is part of an association (base 0)	0.40**	0.06	0.55**	0.11
	(0.158)	(0.129)	(0.237)	(0.140)
Constant	-14.36***	2.14	0.91	-4.40
	(3.776)	(2.851)	(4.257)	(2.809)
Observations	1,032	1,032	1,032	1,032

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13. Probit regression results (Average partial effects): determinants of severe shock incidence by type of shock

	(1)	(2)	(3)	(4)
VARIABLES	Severe climate	Severe violence	Severe prices	Negative COVID

Number of climate shocks		-0.13	0.41***	-0.24**
		(0.115)	(0.122)	(0.119)
Number violence shocks	0.10		0.21***	0.21***
	(0.080)		(0.057)	(0.055)
Number of spoilage shocks	1.21***	0.28	0.38	-0.06
	(0.324)	(0.271)	(0.278)	(0.275)
Number of price shocks	0.50***	0.29***		0.36***
	(0.084)	(0.059)		(0.057)
Negative COVID effect	-0.31	0.19	0.36***	
(base no negative effects)	(0.193)	(0.137)	(0.132)	
Sex (base male)	-1.15**	0.49*	-0.02	-0.16
	(0.557)	(0.269)	(0.307)	(0.265)
Size (base small)	0.08	-0.07	-0.48***	-0.20
	(0.227)	(0.146)	(0.146)	(0.132)
Region (base North)	-0.57	-1.46***	-3.45***	-0.20
	(0.849)	(0.474)	(0.590)	(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	0.84***	0.69***	-0.89***
	(0.215)	(0.169)	(0.168)	(0.181)
Years violence presence	0.03	0.03	0.01	0.00
	(0.042)	(0.023)	(0.021)	(0.026)
Mean rainfall 2021	-0.24	0.36	0.82***	0.38
	(0.369)	(0.262)	(0.208)	(0.236)
Mean temperature 2021	0.18	0.18**	0.39***	-0.01
	(0.117)	(0.086)	(0.078)	(0.077)
Age	-0.01	-0.01	-0.01	-0.02***
	(0.012)	(0.008)	(0.009)	(0.008)
Experience	-0.01	0.03***	0.00	0.01
	(0.014)	(0.009)	(0.010)	(0.009)
Islamic (base: Christian)	-0.20	1.07***	-0.16	-0.19
	(0.354)	(0.302)	(0.298)	(0.244)
Produces own maize (base 0)	-0.35	0.54***	-0.25	0.06
	(0.357)	(0.182)	(0.190)	(0.180)
Is part of an association (base	0.26	0.08	-0.04	0.34**
0)	(0.183)	(0.140)	(0.132)	(0.135)
Constant	-6.74	-8.87***	-14.53***	0.27
	(4.534)	(3.266)	(2.802)	(2.913)
Observations	1,032	1,032	1,032	1,032

Robust standard errors in parentheses

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

First, there is generally a confluence of shocks, particularly in relationship to price shocks. Table 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 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.

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 13 column 1), and a violence shock by 29% (Table 13 column 2). This can be interpreted as higher input and transportation costs constraining traders in their actions to mitigate risk.

Second, there is a positive relationship between COVID and violence shocks. Table 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 regard to region (North versus South), when accounting for severity of shocks, the North is disproportionately affected. Table 12 shows "region" has no effect on the probability of experiencing a climate or spoilage shock, but Southern traders have a higher incidence of violence shocks and Northern traders have a higher incidence of price shocks. But Table 13 shows that Southern traders are less likely to experience severe shocks (when compared with the Northern 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 12 and 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 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. 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 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.

7. 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 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 poor areas. In general, the identification of victims is crucial to developing effective strategies that can help support traders and strengthen security in food systems.

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