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Vulnerability of Nigerian maize traders to a confluence of climate, violence, disease and cost shocks

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Abstract

Purpose – We study five exogenous shocks: climate, violence, price hikes, spoilage and the COVID-19 lockdown. We analyze the association between these shocks and trader characteristics, reflecting trader vulnerability.

Design/methodology/approach – Using primary survey data on 1,100 Nigerian maize traders for 2021 (controlling for shocks in 2017), we use probit models to estimate the probabilities of experiencing climate, violence, disease and cost shocks associated with trader characteristics (gender, size and region) and to estimate the probability of vulnerability (experiencing severe impacts).

Findings – Traders are prone to experiencing more than one shock, which increases the intensity of the shocks. Price shocks are often accompanied by violence, climate and COVID-19 shocks. The poorer northern region is disproportionately affected by shocks. Northern traders experience more price shocks while Southern traders are more affected by violence shocks given their dependence on long supply chains from the north for their maize. Female traders are more likely to experience violent events than men who tend to be more exposed to climate shocks.

Research limitations/implications – The data only permit analysis of the general degree of impact of a shock rather than quantifying lost income.

Originality/value – This paper is the first to analyze the incidence of multiple shocks on grain traders and the unequal distribution of negative impacts. It is the first such in Africa based on a large sample of grain traders from a primary survey.

Keywords Traders, Wholesalers, Maize, Vulnerability, Climate shock, Violence, COVID-19, Nigeria

Paper type Research paper

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1. 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 United Nations (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, 2023) 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.

2. 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 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 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-19 (disease or lockdown). 40% left before 2020 and 60% in 2020 or 2021. Thus, the timing of most dropping was during COVID-19 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-19 and the rise in insecurity.

For our regressions, we used two sources of data for violence and climate shocks. We used Nigeria data from the Armed Conflict Location and Event Data Project (www.acleddata.com) which covers non-state violent actors, locations, fatalities, reported political violence (e.g. abduction, attacks and explosions), sexual violence, looting and property destruction. Temperature and rainfall data were drawn from the "Climate Hazards Group InfraRed Precipitation with Station data," collected by the USA Government (CHIRPS; https://data.chc.ucsb.edu/products/CHIRPS-2.0/).

3. 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

	Number	Share
Total interviews	1,195	100
Maize trader interviews	1,111	93
Traders that stopped trading maize	84%	7%
Gender		
Male	977	88
Female	134	12
Region		
North	1,030	93
South	81	7

Source(s): Authors' calculations from authors' own survey data

Table 1. Maize trader sample characteristics, 2021 survey

Reasons for leaving	Share of traders
Moved on to a more profitable business	51
Unable to secure funds to continue trading	35
Insecurity from herder-farmers conflict	0
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
Contracted COVID-19	0
Movement restrictions during COVID-19 lockdowns	0
Number of traders that stopped trading maize	84

Source(s): Authors' calculations from authors' own survey data

Table 2. Reasons traders exited trading after the 2017 survey and before the 2021 survey

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 focus on impact as all traders were exposed to lockdowns. Each of these shocks was constructed as a summation over subsets of the 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, we recorded the trader as having experienced the general shock (that is, any or all of the types of shocks).

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.

Type of shock	Shocks traders responded to in the survey
Climate	- Delay in receiving maize due to road washout
	- 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 the 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 traders
	- Farmer-herder conflict hurting buying maize from farmers
	- Other insecurity problems (e.g. banditry/kidnappers)
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

Source(s): Authors' own work based on questionnaires used in their own survey

Table 3.
Classification of shocks

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 and 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 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 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-19) 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.

4. Regression model and estimation method

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

$$g_i = \boldsymbol{M_i}\beta_M + \boldsymbol{MV_i}\beta_{MV} + \boldsymbol{X_i}\beta_x + u_i \tag{1}$$

Where g_i is a binary indicator of a violence shock for trader i, where $g_i = 1$ if the trader has experienced that shock in the past year and 0 otherwise.

We proceed in two steps. We estimate general shocks (disregarding severity): (1) climate; (2) violence; (3) spoilage; and (4) higher input prices. We then estimate four shocks which affect severity: (1) climate; (2) violence (3) higher input prices; and (4) COVID-19. We did not include spoilage within the second set of equations due to lack of variability: only 12 traders suffered severe spoilage losses.

M_i is a vector of determinants: (1) size (the scale of the trader's operation), gender, location (north or south) of the main market where the trader sells; (2) the number of shocks (climate, violence, spoilage and input price) experienced by each trader and (3) if the trader experienced a COVID-19-related shock. We did not include the number of times the trader experienced a shock when estimating the probability of experiencing that shock.

MV_i is a vector of county-level variables that include: (1) years of non-state armed actors' presence at the traders' location; and (2) average daily rainfall and temperature for 2021. X_{it} is a vector of control variables, including: (1) trader education, experience, religion, maize production, participation in an association and location (urban vs rural market). We include binary variables concerning whether the trader experienced a violence, price, or general shock in 2017. β_m, β_{MV}, β_x, are the coefficient estimates associated with the study covariates. u_{it} is the error term which we assume is distributed $u_i \mid M_{it}, MV_i, X_i, \sim \mathrm{N}(0,1)$.

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

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

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. We calculate the average partial effects by averaging across the distribution of all observable covariates.

We have used the probit model to accommodate the non-linear relationship between our explanatory variables and the probability of facing these shocks. This contrasts with 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 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 (quantifying the average change in the probability of the event for a one-unit change in each explanatory variable). This allows comparisons between predictors of a trader's probability of facing different shocks [1].

To check the goodness of fit of our model we calculated the Pseudo R-squared (McFadden R-squared) recommended as a measure of goodness of fit for discrete models (Greene, 2006). This 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. A poorly functioning model (where independent variables have no/low explanatory power) will have a pseudo R-squared close to zero. Note that a pseudo R-squared is not the same as an R-squared used in LPM and will have lower values. This implies that even a pseudo R-squared value of 0.2 is considered a good fit (McFadden, 1973).

5. Descriptive statistics

Here we discuss the findings from Tables 4–11. Each table shows the shares of traders having experienced a particular type of shock and their severities.

5.1 Climate/weather shocks

Table 4 shows that 14% of traders experienced a climate/weather shock. Table 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 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 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 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.

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- and north-based traders (Table 5). This may be due to

Table 4. Climate shocks affecting maize traders August 2020–July 2021

	Farm area flood	Farm area drought	Road washout	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

Source(s): Authors' calculations from authors' own survey data

	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-19 effects	61	66	−1.57
	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-19 effects	64	61	0.6

Note(s): *p < 0.1; **p < 0.05; ***p < 0.01
Regions: North includes: Katsina, Kano, Kaduna and Plateau. South includes Oyo
Size: large traders are those that sold 32 tons (or more) per month within the high season
Source(s): Authors' calculations from authors' own survey data

Table 5. Shocks by size and regional base of the maize trader

	Gender (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-19 effects	63	73	−2.27**

Note(s): *p < 0.1; **p < 0.05; ***p < 0.01
Source(s): Authors' calculations from authors' own survey data

Table 6. Shocks by gender of the maize trader

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

	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 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(s): Authors' calculations from authors' own survey's data

Table 7.
Conflict 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				

Source(s): Authors' calculations from authors' own survey data

Table 8.
Spoilage/loss/waste shocks affecting maize traders

in sourcing from certain zones in the north where conflict is higher while the north traders have perhaps more options.

Table 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 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

	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

Source(s): Authors' calculations from authors' own survey data

Table 9. Cost shocks affecting maize traders

Severely affected: If reduced employees, salaries, used own savings, or sold assets	
% Traders severely affected	64
% Traders affected in the north	64
% Traders affected in the south	61

Source(s): Authors' calculations from authors' own survey data

Table 10. COVID-19-related shocks on maize traders: what share were severely affected

	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
Climate +	1	6	15	17	21	11	6	6	11	6				
Violence +	12	16	34	12	17	5	2	1	1	0				
Spoilage +	6	6	19	13	16	16	10	6	3	3				
Price +	10	32	23	19	4	4	4	1	2	0.4	0.8			
COVID-19 +	12	19	17	26	11	8	3	2	1.3	0.8	0.1	0.6	0.7	

Source(s): Authors' calculations from authors' own survey data

Table 11. Shares of traders undergoing no shock, one shock or multiple shocks

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 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 traders were much more likely than males to experience farmer-herder conflict shocks (44–17%) and banditry (54–40%) 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 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.

5.3 Spoilage/loss/waste shocks

Table 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 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 shocks is that presumably all traders face the same or similar fuel prices while maize prices can differ over zones, despite arbitrage.

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 depend on 3PLS for the long supply chains and 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 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.

Table 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 9 shows the effects of the shocks for both price shocks taken together controlling for the trader 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.

5.5 COVID-19-related shocks (mainly from lockdowns)

Since all traders experienced mobility constraints from lockdowns linked to COVID-19, we focus on those traders that were more severely affected. The latter were those who reported doing any of the following: reduced employees or staff salaries, used own savings to weather the shock, or sold own assets. Table 10 shows that 64% of the traders experienced a severe COVID-19-related shock. This was similar in the north and south. There was no significant difference between small and large traders. But female traders were a little more likely to experience the shock (Table 5).

5.6 Confluence of shocks

Table 11 shows the distribution of shocks experienced 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.

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. There are six main findings.

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-19 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. As well, extreme weather events and violent attacks can affect market activity and prices. This is consistent with the literature; for example, Bar-Nahum *et al.* (2020) and Van Den Hoek (2017) show that escalations of violence are correlated with a drop in market prices and market activity. Letta *et al.* (2022) shows that extreme weather events (particularly drought) increase food prices.

Price shocks can also exacerbate the effect of climate and violence shocks. Price shocks increase the probability of experiencing severe climate, violence and COVID-19 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.

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-19 effect (base = no negative effects)	−0.15	0.36***	0.17	0.89***
	(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
McFadden $R2$	0.21	0.176	0.261	0.213

Note(s): Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' own calculations from authors' own survey data

Table 12.
Probit regression (Average partial effects): determinants of shock incidence by type of shock

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.

Variables	(1) Severe climate	(2) Severe violence	(3) Severe prices	(4) Negative COVID-19 effect
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-19 effect (base no negative effects)	−0.31	0.19	0.36***	
	(0.193)	(0.137)	(0.132)	
Gender (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)	0.26	0.08	−0.04	0.34**
	(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
McFadden *R*2	0.307	0.247	0.217	0.154

Note(s): Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' calculations from authors' own survey data

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

Second, there is a positive relationship between COVID-19 and violence shocks. Table 12 shows that traders who experienced a severe COVID-19 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-19 worsened governance standards, including leadership failures which have led to less democratic accountability, high levels of corruption and higher inequality rates (Kaufmann, 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 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 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 12 and 13, there are no significant differences across trader sizes, except on severity of price shocks. Smaller traders are 48% more likely 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. This is consistent with the literature as in the realm of terrorist attacks, women often find themselves bearing a disproportionately heavy burden (Okoli and Nnaemeka 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 even deriving economic gains through trafficking (Bigio and 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 them to violence shocks. The latter may be via the maize farming of traders being mainly in the north where most violence occurs from Boko Haram and farmer-herder conflict. 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, including price, violence, climate and COVID-19 shocks. Second, COVID-19 and violence shocks have a positive relationship, as traders who experienced a severe COVID-19 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-19, 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 *et al.*, 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 1,000 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.

Notes

1. We have selected the probit model over the logit model as we prefer the normality assumption for the error term. However, we confirmed that the results from the probit and logit models are statistically and economically similar.

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