Feed the Future Nigeria Agricultural Policy Activity

NAPA Research Paper 9 September 2023

Nigeria Agricultural Policy Activity

POLICY PREFERENCES IN THE FACE OF WEATHER AND CONFLICT SHOCKS: VIEWS FROM NIGERIAN MAIZE TRADERS

By

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Authors' Acknowledgment:

This report was made possible with support from: the Feed the Future Innovation Lab for Food Security Policy Research, Capacity, and Influence (PRCI) Climate Change Research grant 7200AA19LE000001 RC113673, the USAID/Nigeria funded Food Security Policy Innovation Lab Associate Award, contract number AID1-620-LA-15-00001, the U.S. Department of Agriculture National Institute of Food and Agriculture, and Michigan State University AgBioResearch (project numbers MICL02775, MICL12077, and MICL02593).

This paper is a product of collaborative research funded by the CGIAR Research Program on Policies, Institutions, and Markets (PIM) and the USAID Nigeria mission under the Feed the Future Nigeria Agriculture Policy Activity. The contents are the responsibility of the authors and do not necessarily reflect the views of the funding agencies.

Published by the Department of Agricultural, Food, and Resource Economics, Michigan State University, Justin S. Morrill Hall of Agriculture, 446 West Circle Dr., Room 202, East Lansing, Michigan 48824, USA

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ACRONYMS

BIBD	Balanced Incomplete Block Design
BW	Best-Worst
BWS	Best-Worst Scaling
CIBD	Cyclic Incomplete Block Design
FML	Fractional Multinomial Logit
PBIBDs	Partially (or nearly) Balanced Incomplete Block Designs
RPL	Random Parameters Logit

EXECUTIVE SUMMARY

This study explores the policy preferences of Nigerian maize wholesale traders in response to weather and conflict shocks, which have a significant impact on their maize trading activities and the broader maize value chain in Nigeria. Using a Best-Worst Scaling survey in five major maize-producing and consuming states, we evaluated various policy options, including soft and hard infrastructure-type interventions, to address the challenges related to conflict shocks and weather shocks. The correlated random parameters logit model reveals that maize traders prioritize different policy measures depending on the nature of the shocks they encounter. Additionally, various characteristics, such as gender, business scale, education, and operation region, appear to influence traders' policy preferences. Our analysis highlights the importance of considering heterogeneous preferences in the development of policies aimed at enhancing resilience in the maize value chain.

INTRODUCTION

The agrifood system and value chains in Nigeria have undergone rapid growth and transformation over the last few decades, with maize being a vital crop in the country. Maize is cultivated by 50% of farming households (National Bureau of Statistics, 2019) and is consumed by most people as a staple food, in addition to being an essential ingredient for animal feed (United States Department of Agriculture, 2019). However, as these value chains have expanded and become longer, covering greater geographical distances and involving more actors and segments, they have become increasingly vulnerable to risks induced by various factors such as climate change, insecurity problems, and armed conflicts.

Maize wholesale traders, acting as the crucial link between maize farmers and consumers, play an essential role in the Nigerian maize value chain, supplying maize to approximately 75% of the Nigerian population (Liverpool-Tasie et al., 2017). Despite their pivotal role, there is limited knowledge regarding their preferences and opinions concerning policy interventions in response to risks and shocks that disrupt their maize trading. This lack of understanding is further exacerbated by the absence of policy frameworks that consider the interests and preferences of maize traders. Hence, there is an urgent need for a more inclusive approach to policy design, one that can effectively reduces the vulnerability of maize traders to shocks and mitigates their impacts, while taking into account the perspectives of these traders. Such an approach has the potential to enhance the efficiency and reliability of maize delivery throughout the entire maize value chain.

This study aims to provide insights into the perspectives of Nigerian maize traders regarding policy interventions in response to weather shocks, such as floods and droughts, as well as conflict or insecurity shocks, including Boko Haram conflicts, herder-farmer conflicts, armed robbery or banditry, and kidnapping. These insights can potentially inform policy decisions that can more effectively support both the traders and the maize value chain. To gain a comprehensive understanding of maize traders' perspectives, we surveyed a sample of maize traders in selected provinces of Nigeria and assessed their relative preferences for various policy options designed to address these shocks employing the Best-Worst Scaling (BWS) approach.

The BWS method, initially introduced by Finn and Louviere (1992), has found wide application in evaluating consumer preferences for food values in agricultural marketing literature (Bazzani et al., 2018; Costanigro, Appleby, and Menke, 2013; Lister et al., 2017; Lusk and Briggeman, 2009), as well as preferences of the public and producers for food production practices (McKendree, Tonsor, and Wolf, 2018), and policy preferences of the public (Stone, Costanigro, and Goemans, 2018), consumers (Caputo and Lusk, 2019), farmers (Ola and Menapace, 2020; Ortega et al., 2015; Wolf and Tonsor, 2013; Maredia et al., 2022; Mason et al., 2019), and other agricultural stakeholders (Maredia et al., 2022; Mason et al., 2019) in the agricultural and food policy literature. However, there is a notable gap in the existing literature regarding the assessment of policy preferences among midstream actors in agrifood value chains. The exception is Maredia et al.'s (2022) examination of crop millers and traders' preferences for COVID-19 pandemic recovery policies. To the best of our knowledge, this study is the first to evaluate policy preferences among midstream actors in agrifood value chains in the context of weather shocks and conflict shocks, including those related to insecurity.

We examine various policy options for addressing weather shocks and conflict shocks, including financial, information, and security policies as soft infrastructure-type measures, as well as safety and energy infrastructure as hard infrastructure-type measures. We analyze maize traders' preferences for each type of shock and within different subgroups, highlighting the importance of tailoring policy responses to the nature of the shocks and specific characteristics of traders.

BACKGROUND AND POLICY IDENTIFICATION

Jaffee, Siegel, and Andrews (2010) developed a conceptual framework for identifying risks within agricultural value chains, assessing participants' exposure to, and potential losses from, these risks. Primary risks encountered by agricultural value chains include extreme weather events such as floods and droughts, hurricanes, and earthquakes, as well as logistical and infrastructural risks involving physical destruction, conflicts, and changes in transportation. Of particular focus among these risks are weather and conflict-related shocks, which are increasingly prevalent in many countries, including Nigeria (Nogales and Oldiges, 2023; Ojo, Oyewole, and Aina, 2023).

Extreme weather events and violent conflicts, including insecurity issues, can impact agricultural systems and value chains at multiple stages, affecting production, harvest, storage, and transportation (Dercon, 2002; Gommes, 1998; Lobell and Field, 2007; Lobell, Schlenker, and Costa-Roberts, 2011; Liverpool-Tasie and Parkhi, 2021), all of which have influence on maize traders. For example, floods or droughts in the upstream production area can affect the availability of maize, subsequently influencing traders' maize purchases. Floods, in particular, can harm traders' maize storage by increasing the likelihood of pest infestations or mold growth (Liverpool-Tasie and Parkhi, 2021), and they can also disrupt maize transportation by causing road washouts. Violent conflicts can similarly disrupt entire value chains, from production areas to transportation routes and markets, which constrains traders' ability to buy and sell maize. A recent survey of Nigerian maize wholesale traders reveals that 13% of traders in the northern region and 26% of traders in the southern region experienced disruptions caused by floods and droughts between August 2020 and July 2021 (Vargas, Reardon, and Liverpool-Tasie, 2023). Additionally, it was observed that nearly half of the traders were affected by violent conflicts during the same period.

The set of risk management tools proposed by Jaffee, Siegel, and Andrews (2010) includes (i) financial instruments; (ii) enterprise management practices; (iii) technology development and adoption; (iv) policy and public programs; and (v) investment in infrastructure. We have examined these five instruments from a Nigerian policy perspective based on government documents and inputs from Nigerian maize traders and categorized them into two broad policy typologies: soft and hard infrastructures. As a result, we have identified nine policy options for addressing conflict shocks and eight policy options for addressing weather shocks, all of which fall under these five categories. The policy options are outlined in Table 1.

Table 1. Risk management instruments and policy options

Risk management instruments	Typology of policies	Policy options for conflict shocks *(Short name)*	Policy options for weather shocks *(Short name)*
Financial instruments	Soft infrastructure - Finance	Conflict cash relief *("Cash relief")*	Weather cash relief *("Cash relief")*
		Conflict insurance *("Insurance")*	Weather insurance *("Insurance")*
		Loans for investment in technology to prevent conflict losses (e.g., security camera) *("Loans")*	Loans for investment in technology to prevent weather losses (e.g., better storage facility) *("Loans")*
Enterprise management practices	Soft infrastructure - Information	Call center for real-time information on the safety of routes *("Call center")*	Call center for real-time information on flooded roads and alternative routes *("Call center")*
Technology development and adoption		Training in technologies to minimize conflict losses (e.g., strategies to diversify suppliers) *("Training")*	Training in technologies to deal with weather effects (e.g., mold growth prevention) *("Training")*
Policy and public programs	Soft infrastructure - Security operations	More functional security on the roads *("Road security")*	-
		More functional security in the market/warehouse area *("Market/warehouse security")*	-
Investments in infrastructure	Hard infrastructure - Transit	-	More functional dams, culverts, or drainage on the roads *("Road infrastructure")*
	Hard infrastructure - Market and warehouse area	More functional safety concrete barriers in the market/warehouse area *("Market/warehouse infrastructure")*	More functional flood barriers, sandbags, or tarps in the market/ warehouse area *("Market/warehouse infrastructure")*
	Hard infrastructure - Energy access	More functional electricity in the market/warehouse area (e.g., for reliable lighting) *("Market/warehouse energy")*	More functional electricity in the market/warehouse area (e.g., for temperature-controlled warehouses) *("Market/warehouse energy")*

Notes: Interviewers read the full policy options to the respondents. The short names in the parentheses are abbreviations that will be used throughout the rest of the paper.

Soft infrastructure-type policy options include financial policies and policies aimed at enhancing access to information and security operations. Financial policies involve offering cash assistance to traders who have incurred losses due to weather or conflict shocks, enhancing access to insurance and the coverage to protect against potential losses from these shocks, and facilitating access to loans that traders can invest in technologies to prevent losses from these shocks. Policies to improve information access include providing real-time information via the development of early warning systems (call centers) and strengthening traders' capacity through training. Additionally, the provision of enhanced security on roads and in market or warehouse areas are included to address conflict shocks. On the other hand, hard infrastructure-type policy options encompass the construction or improvement of road infrastructure, protection hardware for markets and warehouses, and energy infrastructure.

DATA AND SURVEY DESIGN

We designed a survey to collect data from a sample of Nigerian maize wholesale traders, focusing on their maize purchases and sales, their encounters with disruptions caused by weather and conflict shocks, and their relative preferences for policy options to address these shocks. We conducted in-person interviews between May and August 2023 with a total of 300 maize wholesale traders, representing a sub-sample drawn from previous surveys involving maize traders.

The initial maize trader survey in Nigeria occurred in 2017, including 1,405 maize traders in the primary maize-producing states in northern Nigeria (Kaduna, Kano, Katsina, and Plateau), as well as the key maize-consuming state in southern Nigeria (Oyo). Within each state, all maize traders in the primary city markets were interviewed. In addition, in the four northern states, traders from the top five regional markets with the highest total maize sales volume were listed and categorized into two groups: the "large trader stratum" with maize sales exceeding 32 tons during a typical month in the high maize trading season (from August to February), and the "small trader stratum" with maize sales below 32 tons during the same period. Traders were then randomly selected based on the proportion of small and large traders in each market.

In 2021, 1,111 traders from the 2017 sample were re-surveyed, including 584 traders from Kano, 138 traders from Kaduna, 170 traders from Katsina, 137 traders from Plateau, and 80 traders from Oyo. For this study, we randomly selected 60 maize traders from each of the five states (a total of 300) and conducted an additional survey to gain a more in-depth understanding of their experience with shocks between August 2020 and July 2021, as well as their policy preferences.[1]

We developed a Best-Worst Scaling (BWS) experiment to elicit maize traders' preferences for alternative policy options regarding weather and conflict shocks. This experiment aimed to understand how traders make trade-offs among competing options, as they select the best and worst choices from a choice set. Additionally, it sought to comprehend how traders prioritize overall policy options through both ordinal and cardinal rankings.

Balanced Incomplete Block Design (BIBD) is frequently used in experimental designs for object case BWS surveys (Bazzani et al., 2018; Louviere, Flynn, and Marley, 2015). Balance is achieved by

[1] If the randomly selected trader was unavailable for an interview due to reasons such as death or being unreachable, we substituted them with another randomly selected trader from the same state.

ensuring that each choice set contains an equal number of objects (policy options) that are repeated an equal number of times across all the choice sets. Furthermore, the objects are allocated orthogonally, implying each object appears together with other objects an equal frequency across the choice sets. However, generating a BIBD may lead to numerous choice sets, potentially causing respondent fatigue (Bazzani et al., 2018). Therefore, we opted to use a generalized Cyclic Incomplete Block Design (CIBD) (Jarrett and Hall, 1978; John, 1981), which is a class of Partially (or nearly) Balanced Incomplete Block Designs (PBIBDs) that relaxes the orthogonality requirement. CIBDs are easy to construct, possess good statistical properties, and the analysis of them is the same as the analysis of BIBDs (Lawson, 2014).

The design resulted in nine BWS choice sets for conflict shocks and eight BWS choice sets for weather shocks. Each choice set contains four policy options, and each policy option is repeated four times across the nine (eight) questions. In addition, each policy option has four (five) first associates and four (two) second associates for the conflict (weather) shock BWS choice sets. First associates occur together in a choice set two times, and second associates occur together in a choice set one time, maximizing D-efficiency (D-optimal).

In each BWS choice set, traders were asked to select the best (most preferred) and worst (least preferred) policy option. An example of BWS choice set for conflict and weather shock is provided in Figure 1.

Example of a BWS choice set for conflict and weather shocks

Each question is composed of four policy options that could be implemented to address disruptions in maize trading due to conflict or insecurity shocks. Conflict or insecurity shocks refer to Boko Haram conflicts, herder-farmer conflicts, armed robbery or banditry, and kidnapping. For each question we would like to know which policy option you think is the best or most preferred, and which is the worst or least preferred.

In your opinion, which of the following policy options is the best way to prevent or protect losses from conflict or insecurity shocks, and which policy option is the worst way to do so?		
Most Preferred	Policy	Least Preferred
O	More functional security on the roads	**O**
O	More functional electricity in the market/warehouse area (e.g., for reliable lighting)	**O**
O	Conflict insurance	**O**
O	More functional security in the market/warehouse area	**O**

Each question is composed of four policy options that could be implemented to address disruptions in maize trading due to weather shocks. Weather shocks refer to floods or droughts. For each question we would like to know which policy option you think is the best or most preferred, and which is the worst or least preferred.

In your opinion, which of the following policy options is the best way to prevent or protect losses from weather shocks, and which policy option is the worst way to do so?		
Most Preferred	Policy	Least Preferred
O	Weather insurance	**O**
O	Training in technologies to deal with weather effects (e.g., mold growth prevention)	**O**
O	Call center for real-time information on flooded roads and alternative routes	**O**
O	More functional dams, culverts, or drainage on the roads	**O**

Figure 1. Example of a BWS choice set for conflict and weather shock policies

EMPIRICAL STRATEGY

The count method serves as the initial step for analyzing BWS data (Louviere, Flynn, and Marley, 2015). Initially, we counted how many times each policy option was selected as the best and the worst across all choice sets and respondents. Subsequently, we calculated the Best-Worst (BW) score for each policy option by the difference between the best and the worst counts. The policy with the lowest BW score is used as the reference policy in the empirical model.

The assumption underlying the BWS approach is that respondents choose the best and worst options within a choice set so that the difference in latent scale between the selected pair of options is maximized (Flynn and Marley, 2015). If there are J options in a choice set, there are $J(J-1)$ possible best-worst pairs, from which the respondent n can make a choice. In our study, with four policy options in each choice set, there are 12 such pairs. Employing random utility theory (McFadden, 1974), which underpins the BWS method, respondents choose pair j and $i\ (\neq j)$ as the best and worst policy options, respectively, to maximize utility:

$$U_{nji} = \beta_j - \beta_i + \varepsilon_{nji}, \tag{1}$$

where ε_{nji} is the random error term, and β_j (β_i) is the importance parameter of policy option j (i) relative to a reference policy option whose importance parameter is normalized to zero.

The probability of a respondent choosing the combination j and i in a choice set s equals the probability that the utility from this combination, U_{nji}, is greater than the utilities from all the other possible $J(J-1)-1$ combinations. Assuming the random error term follows the extreme value type I distribution, we estimate Random Parameters Logit (RPL) models, allowing preferences for policy options to vary across respondents. The unconditional probability of respondent n selecting policy option j and i as the best and the worst from J options over S choice sets is represented as:

$$P_{nji} = \int_{\beta} \prod_{s=1}^{S} \frac{e^{[\beta_{njs}-\beta_{nis}]}}{\sum_{m=1}^{J}\sum_{k=1}^{J} e^{[\beta_{nms}-\beta_{nks}]-J}} f(\beta_n) d\beta_n, \tag{2}$$

where $f(\beta_n)$ denotes the density function of the importance parameters β_n, which we assume to have a normal distribution and can be fully correlated. We estimate the parameters employing simulated maximum likelihood estimation with the use of Halton draws (Bhat, 2001; Train, 2009). Subsequently, based on the estimated parameters, we derive the share of preferences for each policy option m (SOP_m) using the bootstrapping method by Krinsky and Robb (1986):

$$SOP_m = \frac{e^{\widehat{\beta}_m}}{\sum_{k=1}^{J} e^{\widehat{\beta}_k}} \tag{3}$$

We report the mean and standard errors of the shares of preferences for each policy option. The share of preferences for each option is the predicted probability of that option being selected as the best, and these shares of preferences must add up to one across all the options, such as the nine (eight) policy options related to conflict (weather) shocks (Lusk and Briggeman, 2009). These shares of preferences offer insights into the importance of each policy option relative to the others and provide cardinal interpretations. For example, if the share of preferences for policy j is three times that of policy i, it can be interpreted that policy j is three times as important as policy i.

Additionally, we compute the individual-specific share of preferences for each policy using individual-specific parameter estimates derived from the RPL model and the actual choices made by each individual. The share of preferences for individual n and policy m, sop_{nm}, is bounded ($0 \leq sop_{nm} \leq 1$), and for each individual, the shares of preferences over the J policies sum up to 1 ($\sum_{k=1}^{J} sop_{nk} = 1$). Using these individual-specific shares of preferences for the nine (eight) conflict (weather) shock policies as dependent variables, we employ a Fractional Multinomial Logit (FML) model (Papke and Wooldridge, 1996) to investigate the relationship between individual characteristics ($\boldsymbol{x}_n$) and their policy preferences. The FML model, with the coefficient of a base policy normalized to zero (typically the coefficient of the first equation, $\alpha_1 = 0$), is represented as:

$$sop_{nm} = \frac{e^{\alpha_m x_n}}{1+\sum_{k=2}^{J} e^{\alpha_k x_n}} \tag{4}$$

The coefficients, $\boldsymbol{\alpha}$, are estimated by the quasi-maximum likelihood estimation (Papke and Wooldridge, 1996). Explanatory variables ($\boldsymbol{x}$) include traders' gender, education, region, operational scale, years of trading, and engagement in other income-generating jobs (discussed below).

RESULTS

The basic characteristics of maize traders are summarized in Table 2. Nine traders transitioned out of maize trading between the 2021 maize trader survey and the current 2023 BWS survey.[2] On average, traders are 47 years old, and approximately 80% of them are male. About 65% of traders have completed formal education, either at the primary, secondary, or university level. Additionally, 55% of traders are classified as large-scale traders with monthly maize sales exceeding 32 metric tons during the high-volume maize trading period from August 2020 to February 2021. The majority of the traders (about 90%) did not engage in other income-generating jobs between August 2020 and July 2021.

Regional distribution indicates that 80% of traders are located in the northern region, including Kaduna, Kano, Katsina, and Plateau, while the remaining 20% are located in the southern region, specifically Oyo. The average trading experience of traders is nearly 23 years. Notably, only 15% and 3% of the traders reported experiencing any of the conflict shocks and weather shocks, respectively, during the reference period from August 2020 to July 2021.

[2] Although these traders are no longer engaged in maize trading, we retained them for participation in the BW choice sets, without collecting additional demographic or maize trading characteristics data.

Table 2. Summary statistics of maize traders' characteristics

Variable	Definition	Obs.	Mean	Std. Dev.
Maize trading	1 = Engaging in maize trading business	300	0.97	0.17
Age	Age in years	291	47.36	10.27
Gender	1 = Male	291	0.80	0.40
Education	1 = Completed formal education (primary, secondary, or university)	291	0.65	0.48
Scale	1 = Large (monthly sales > 32 tons during high maize trading season, Aug. 2020 - Feb. 2021)	291	0.55	0.50
Other job	1 = Engaged in other income-generating jobs between Aug. 2020 and Jul. 2021	300	0.11	0.31
Region	1 = North, 0 = South	300	0.80	0.40
Years of trading	Years of trading experience	295	22.60	8.88
Conflict shock	1 = Experienced any Boko Haram conflict, herder-farmer conflict, armed robbery/banditry, or kidnapping between Aug. 2020 and Jul. 2021	291	0.15	0.36
Weather shock	1 = Experienced any flood or drought between Aug. 2020 and Jul. 2021	291	0.03	0.17

To estimate the random parameter logit model, we used the call center policy option as the reference for both conflict and weather shock policies, guided by the lowest BW scores in Table 3. The results of the correlated RPL models are reported in Tables 4 and 5, and they are largely in line with the descriptive findings derived from the BW scores.[3] The shares of preferences for both conflict and weather shock policies reveal that cash relief is the most favored policy option. This preference for cash relief is in contrast to the findings of Maredia et al. (2022), where cash transfers as part of the COVID-19 pandemic recovery were rated among the least preferred policies for crop traders in Myanmar. It is plausible that Nigerian maize traders have become somewhat accustomed to dealing with conflict and weather shocks, which are recurrent issues in Nigeria, hence favor the flexibility of cash relief in responding to various needs.

As for both conflict and weather shocks, the least preferred policy option is the establishment of call centers for real-time information, which served as the reference policy. Beyond call centers, training and loans rank among the lowest three policies for conflict shocks, while training and market/warehouse energy occupy the bottom three positions for weather shocks.

[3] We performed the likelihood ratio test between uncorrelated and correlated RPL models, rejecting the null hypothesis of uncorrelated parameters, and present the results of the correlated RPL models.

Table 3. Best-worst scores for conflict and weather shock policies

		Best counts (B)	Worst counts (W)	BW score (B-W)
Conflict shock policies				
Soft infra-structure	Cash relief	752	66	686
	Call center	58	590	-532
	Training	108	329	-221
	Road security	530	106	424
	Insurance	196	442	-246
	Loans	121	548	-427
	Market/warehouse security	456	90	366
Hard infra-structure	Market/warehouse infrastructure	337	168	169
	Market/warehouse energy	142	361	-219
	Number of choices made (9 choice sets for 300 traders)	2,700	2,700	
Weather shock policies				
Soft infra-structure	Cash relief	688	88	600
	Loans	228	362	-134
	Insurance	209	447	-238
	Call center	89	466	-377
	Training	88	374	-286
Hard infra-structure	Road infrastructure	599	111	488
	Market/warehouse infrastructure	392	130	262
	Market/warehouse energy	107	422	-315
	Number of choices made (8 choice sets for 300 traders)	2,400	2,400	

In addition to the widely favored cash relief option, traders' preferences exhibit an interesting trend where they prioritize different types of policy options depending on the nature of the shocks they face. For instance, in response to conflict shocks, traders tend to place a higher emphasis on policy options related to creating a secure environment (i.e., road security and market/warehouse security), which are categorized as soft infrastructure-type policies, followed by a hard infrastructure-type policy option (i.e., market/warehouse infrastructure). This preference may arise from their experiences with the security challenges resulting from violent conflicts, leading them to prioritize enhanced security measures on roads and in market/warehouse areas (such as the deployment of trained security personnel).

On the other hand, when confronting weather shocks, traders appear to predominantly prioritize road and market/warehouse infrastructure, which fall under the category of hard infrastructure-type policies. This is followed by soft infrastructure-type financial policy options (i.e., loan and insurance). This preference shift could be attributed to the physical and logistical challenges brought by adverse weather conditions, which require more tangible solutions to safeguard their trading activities. Notably, road infrastructure (26.8%) is deemed more crucial than market/warehouse infrastructure (16%), suggesting that challenges arising from road washouts due to floods pose a considerable obstacle for traders (Table 5).

Table 4. Correlated RPL model results for conflict shock policies

	Conflict shock policies	Mean	Std. Dev.	Share of preferences (%)
Soft	Cash relief	2.501***	0.753***	34.5
		(0.082)	(0.076)	(0.014)
	Call center - **BASE**	0.000	-	2.8
				(0.002)
	Training	0.336***	0.489***	4.0
		(0.065)	(0.060)	(0.002)
	Road security	1.828***	0.861***	17.6
		(0.073)	(0.067)	(0.008)
	Insurance	0.474***	1.264***	4.6
		(0.071)	(0.075)	(0.003)
	Loans	0.254***	0.897***	3.7
		(0.071)	(0.069)	(0.002)
	Market/warehouse security	1.777***	0.640***	16.8
		(0.072)	(0.066)	(0.008)
Hard	Market/warehouse infrastructure	1.310***	0.516***	10.5
		(0.071)	(0.064)	(0.005)
	Market/warehouse energy	0.679***	0.918***	5.6
		(0.069)	(0.065)	(0.003)
	Sum of share of preferences			100%
	Number of traders	300		
	Number of observations (N)	2,700		
	Log likelihood function (LLF)	-5,228.107		
	Akaike Information Criterion (AIC) / N	3.905		
	Bayesian Information Criterion (BIC) / N	4.001		

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Table 5. Correlated RPL model results for weather shock policies

	Weather shock policies	Mean	Std. Dev.	Share of preferences (%)
Soft	Cash relief	2.277***	0.711***	35.4
		(0.080)	(0.090)	(0.014)
	Loans	0.340***	0.762***	5.1
		(0.065)	(0.079)	(0.003)
	Insurance	0.217***	1.263***	4.5
		(0.068)	(0.081)	(0.003)
	Call center - **BASE**	0.000	-	3.6
				(0.002)
	Training	0.140**	0.493***	4.2
		(0.065)	(0.069)	(0.003)
Hard	Road infrastructure	1.999***	1.592***	26.8
		(0.076)	(0.069)	(0.011)
	Market/warehouse infrastructure	1.482***	1.263***	16.0
		(0.072)	(0.065)	(0.007)
	Market/warehouse energy	0.167**	0.560***	4.3
		(0.068)	(0.075)	(0.002)
	Sum of share of preferences			100%
	Number of traders	300		
	N	2,400		
	LLF	-4,684.102		
	AIC / N	3.933		
	BIC / N	4.017		

Notes: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

The application of the FML model enhances our understanding of the factors influencing maize traders' policy preferences in the face of conflict and weather shocks. Tables 6 and 7 present the marginal effects of traders' characteristics on the share of preferences. Notably, various trader characteristics affect the share of preferences for insurance in response to conflict shocks (Table 6). Male traders exhibit a decreasing share of preference for insurance, while large-scale traders, formally educated traders, and traders in the northern region display an increasing share of preferences. Large-scale traders are likely to have greater incentives to safeguard their business through formal measures, such as insurance, compared to small-scale traders. Similarly, formally educated traders may possess a better understanding of the potential impact of unforeseen conflicts, leading them to perceive insurance as a crucial risk management strategy. Another interesting observation pertains to the preferences for road security in response to conflict shocks, where the share of preferences increases for traders in the southern region compared to those in the northern region. Given that southern traders typically cover longer distances to source maize from the northern maize-producing region, prioritizing road security becomes a logical choice for them.

Table 6. Marginal effects from the FML model for conflict shock policies

	Soft infrastructure						*Hard infrastructure*	
	Finance			*Information*	*Security operations*			
VARIABLES	(1) Cash relief	(2) Insurance	(3) Loans	(4) Training	(5) Road security	(6) Market/warehouse security	(7) Market/warehouse infrastructure	(8) Market/warehouse energy
1 = Male	0.0702**	-0.0698**	0.0071	0.0010	0.0149	-0.0156*	-0.0146**	0.0087
	(0.0284)	(0.0274)	(0.0055)	(0.0037)	(0.0133)	(0.0093)	(0.0068)	(0.0078)
1 = Large-scale	-0.0213	0.0257**	-0.0118**	-0.0043*	0.0103	0.0088	0.0025	-0.0093
	(0.0222)	(0.0104)	(0.0046)	(0.0026)	(0.0095)	(0.0074)	(0.0047)	(0.0060)
1 = Formally educated	-0.0277	0.0189**	0.0098**	0.0081***	-0.0204**	-0.0022	0.0028	0.0086*
	(0.0223)	(0.0095)	(0.0038)	(0.0024)	(0.0095)	(0.0077)	(0.0048)	(0.0045)
1 = Engaged in other job	-0.0257	0.0203	-0.0045	-0.0014	0.0045	0.0038	0.0091	-0.0076
	(0.0280)	(0.0144)	(0.0054)	(0.0039)	(0.0140)	(0.0096)	(0.0077)	(0.0073)
1 = North	-0.0008	0.0410***	0.0045	0.0041	-0.0475***	0.0014	0.0080	-0.0151*
	(0.0321)	(0.0155)	(0.0069)	(0.0039)	(0.0176)	(0.0099)	(0.0065)	(0.0089)
Years of trading	-6.11e-06	-0.0003	-3.11e-05	2.08e-05	5.41e-05	0.0002	-4.06e-05	4.67e-05
	(0.0012)	(0.0005)	(0.0002)	(0.0002)	(0.0005)	(0.0004)	(0.0002)	(0.0002)
Observations	286	286	286	286	286	286	286	286

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Call center is the base policy.

Table 7. Marginal effects from the FML model for weather shock policies

	Soft infrastructure				*Hard infrastructure*		
	Finance			*Information*			
VARIABLES	(1) Cash relief	(2) Insurance	(3) Loans	(4) Training	(5) Road infrastructure	(6) Market/warehouse infrastructure	(7) Market/warehouse energy
1 = Male	0.0524**	-0.0106	0.0235**	0.0162***	-0.0927***	-0.0190**	0.0193***
	(0.0230)	(0.0070)	(0.0091)	(0.0048)	(0.0268)	(0.0074)	(0.0046)
1 = Large-scale	0.0027	0.0115**	-0.0200**	-0.0115***	0.0326*	0.0044	-0.0130***
	(0.0152)	(0.0048)	(0.0081)	(0.0042)	(0.0177)	(0.0058)	(0.0041)
1 = Formally educated	-0.0142	0.0025	0.0052	0.0026	-0.0004	0.0043	-0.0003
	(0.0158)	(0.0052)	(0.0081)	(0.0043)	(0.0179)	(0.0061)	(0.0047)
1 = Engaged in other job	0.0065	0.0070	-0.0181*	-0.0094*	0.0172	0.0062	-0.0058
	(0.0227)	(0.0080)	(0.0095)	(0.0052)	(0.0259)	(0.0086)	(0.0074)
1 = North	-0.0699***	0.0074	-0.0307**	-0.0170***	0.112***	0.0335***	-0.0233***
	(0.0250)	(0.0061)	(0.0139)	(0.0062)	(0.0220)	(0.0084)	(0.0067)
Years of trading	0.0005	0.0001	-0.0003	-7.68e-05	-0.0002	-3.65e-05	-7.85e-05
	(0.0008)	(0.0003)	(0.0004)	(0.0002)	(0.0009)	(0.0003)	(0.0002)
Observations	286	286	286	286	286	286	286

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Call center is the base policy.

Concerning the determinants of policy preferences in response to weather shocks (Table 7), the gender of the trader stands out as a significant determinant influencing policy preferences, affecting the share of preferences for all policies except insurance. Specifically, male traders exhibit a decreasing share of preferences for road and market/warehouse infrastructure, implying an increase in the share of preferences among female traders for these hard infrastructures. Additionally, similar to the observations related to conflict shock policies, large-scale traders again show an increasing share of preferences for insurance compared to small-scale traders. However, the education level does not seem to affect preferences for weather shock policies.

Given the varying policy preferences, we categorized the sample into various subgroups to explore heterogeneity in policy preferences across traders with different characteristics. These subgroups were defined based on gender (female/male), business scale (large/small), educational background (formally educated/uneducated), region (North/South), and experience with conflict shocks (yes/no).[4] Using the estimated parameters obtained from the correlated RPL models, we computed the shares of preferences for each subgroup (Tables 8 and 9). Detailed results can be found in Appendix Tables A.1 through A.9.

The preferences for conflict shock policies among subgroups largely align with the overall policy preferences of the full sample. While cash relief remains the most favored policy among female traders (26.1%), their preference is more evenly distributed to market/warehouse security (23.7%) and road security (20.5%) compared to male traders, who place significant importance on cash relief (34.4%) and much less on road security (17.6%) and market/warehouse security (15.9%). This divergence may arise from the fact that women are generally more vulnerable to violent conflicts (Isola and Tolulope, 2022), leading them to prioritize preventive measures.

In terms of regional subgroups, North and South, traders in the North ranked cash relief as their most preferred policy (34.9%), followed by market/warehouse security (17.0%) and road security (15.5%). Conversely, traders in the South prioritized road security (26.3%) over cash relief (21.6%) and market/warehouse security (18.7%), consistent with the findings from the FML model. This difference can be attributed to the fact that maize is primarily produced in the northern part of the country. Therefore, southern traders depend on the North for sourcing maize, resulting in longer transit distances, which increases the importance of road security.

4 While we attempted to create subgroups based on prior experience with weather shocks, only nine traders in our sample reported having encountered such shocks, hence, we were unable to proceed with this subgroup analysis due to the small number of observations.

Table 8. Share of preferences by sub-groups for conflict shock policies

	Conflict shock policies	Share of preferences (%)									
		Gender		Scale		Education		Region		Conflict shock	
		Female	Male	Large	Small	Educated	Un-educated	North	South	Yes	No
Soft	Cash relief	26.1 (0.027)	34.4 (0.015)	32.3 (0.017)	33.5 (0.021)	27.6 (0.014)	47.9 (0.031)	34.9 (0.015)	21.6 (0.030)	34.3 (0.038)	31.6 (0.014)
	Call center - **BASE**	2.2 (0.003)	2.8 (0.002)	2.5 (0.002)	2.8 (0.003)	3.5 (0.002)	1.7 (0.002)	2.7 (0.002)	2.8 (0.004)	2.5 (0.004)	3.1 (0.002)
	Training	2.6 (0.004)	4.3 (0.003)	4.0 (0.003)	4.3 (0.004)	5.4 (0.003)	2.5 (0.003)	4.2 (0.003)	2.6 (0.004)	5.0 (0.008)	4.4 (0.003)
	Road security	20.5 (0.024)	17.6 (0.009)	15.4 (0.010)	18.7 (0.013)	17.8 (0.009)	14.8 (0.014)	15.5 (0.008)	26.3 (0.028)	22.0 (0.029)	16.6 (0.008)
	Insurance	6.9 (0.010)	4.1 (0.003)	6.9 (0.005)	3.5 (0.003)	5.6 (0.004)	2.6 (0.003)	4.6 (0.003)	4.3 (0.006)	2.6 (0.005)	5.4 (0.004)
	Loans	2.1 (0.003)	4.3 (0.003)	4.6 (0.004)	3.2 (0.003)	4.7 (0.003)	3.6 (0.004)	3.9 (0.003)	2.1 (0.003)	5.8 (0.009)	4.4 (0.003)
	Market/ warehouse security	23.7 (0.025)	15.9 (0.008)	17.3 (0.011)	17.6 (0.012)	17.4 (0.009)	12.1 (0.012)	17.0 (0.008)	18.7 (0.023)	13.8 (0.018)	17.1 (0.008)
Hard	Market/ Warehouse infrastructure	9.5 (0.011)	11.1 (0.006)	12.9 (0.008)	9.5 (0.007)	10.9 (0.006)	10.8 (0.011)	13.3 (0.007)	3.7 (0.005)	8.4 (0.011)	11.3 (0.006)
	Market/ warehouse energy	6.4 (0.008)	5.5 (0.003)	4.1 (0.003)	6.7 (0.005)	7.1 (0.004)	3.9 (0.004)	3.9 (0.003)	18.0 (0.021)	5.6 (0.009)	6.0 (0.003)
Sum of share of preferences (%)		100	100	100	100	100	100	100	100	100	100
Number of observations		59	232	159	132	190	101	240	60	45	246

Notes: Standard errors in parentheses. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Table 9. Share of preferences by sub-groups for weather shock policies

	Weather shock policies	Share of preferences (%)							
		Gender		Scale		Education		Region	
		Female	Male	Large	Small	Educated	Uneducated	North	South
Soft	Cash relief	24.3 (0.024)	33.7 (0.015)	32.8 (0.018)	36.0 (0.020)	28.9 (0.014)	46.8 (0.028)	32.6 (0.014)	69.6 (0.052)
	Loans	4.7 (0.006)	5.4 (0.003)	4.4 (0.004)	6.3 (0.005)	8.2 (0.005)	2.7 (0.003)	4.3 (0.003)	2.2 (0.005)
	Insurance	5.6 (0.008)	3.4 (0.002)	5.7 (0.005)	3.6 (0.003)	5.0 (0.003)	3.2 (0.004)	4.7 (0.003)	2.3 (0.005)
	Call center - **BASE**	3.9 (0.005)	3.5 (0.002)	3.3 (0.003)	4.5 (0.004)	4.4 (0.003)	2.6 (0.003)	3.2 (0.002)	2.1 (0.005)
	Training	4.0 (0.006)	3.8 (0.003)	3.7 (0.003)	5.1 (0.004)	5.7 (0.004)	2.3 (0.003)	3.5 (0.002)	2.4 (0.005)
Hard	Road infrastructure	36.2 (0.034)	28.5 (0.014)	29.8 (0.017)	24.1 (0.016)	27.1 (0.014)	23.6 (0.020)	29.6 (0.013)	11.3 (0.021)
	Market/warehouse infrastructure	16.2 (0.017)	17.5 (0.010)	16.7 (0.011)	14.4 (0.010)	15.4 (0.009)	15.9 (0.015)	19.1 (0.010)	4.7 (0.010)
	Market/warehouse energy	5.0 (0.007)	4.2 (0.003)	3.6 (0.003)	5.9 (0.005)	5.3 (0.004)	3.0 (0.004)	3.1 (0.002)	5.4 (0.011)
Sum of share of preferences (%)		100	100	100	100	100	100	100	100
Number of observations		59	232	159	132	190	101	240	60

Notes: Standard errors in parentheses. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Regarding weather shock policies, it is notable that female traders predominantly favored road infrastructure (36.2%) over cash relief (24.3%), while male traders preferred cash relief (33.7%) to road infrastructure (28.5%). This once again reflects that female traders prioritize preventive measures (i.e., dams, culverts, or drainage) compared to ex-post cash relief, which could address immediate financial needs but may not offer the same level of broader risk mitigation.

In addition, educated traders tend to assign much less priority to cash relief (28.9%) compared to uneducated traders (46.8%). For traders in the South, there is a relatively higher emphasis on road infrastructure (11.3%) compared to market/warehouse infrastructure (4.7%), while traders in the North place relatively less priority on road infrastructure (29.6%) compared to market/warehouse infrastructure (19.1%). As discussed before, this divergence is likely due to the longer transit distances that southern traders must cover compared to their northern counterparts, which leads to a higher emphasis on safety measures during travel.

CONCLUSION

In this study, we examined the preferences of Nigerian maize wholesale traders concerning policies designed to mitigate the impacts of weather and conflict shocks, which significantly affect their maize trading activities and, by extension, the entire maize value chain. Despite the pivotal role played by maize traders in connecting upstream producers and downstream consumers, the development of policies addressing the disruptions they encounter and incorporating their perspectives has been largely overlooked.

By implementing a BWS survey in major maize-producing and consuming states in Nigeria, we evaluated nine distinct policy options to manage the challenges posed by conflict shocks and another eight options for addressing weather shocks. Utilizing a correlated RPL model, we found that when faced with conflict shocks, traders tend to prioritize soft infrastructure-type security measures over hard infrastructure-type interventions. In contrast, when dealing with weather shocks, the priority shifts to hard infrastructure measures over soft infrastructure ones. This reveals that traders' policy preferences vary depending on the nature of the shocks they are facing.

Additionally, our subgroup analyses show that various factors, including gender, business scale, educational background, region of operation, and prior exposure to shocks, influence the shaping of traders' perspectives on the ideal strategies for addressing these shocks. This heterogeneity among maize traders underscores the need for tailored, context-specific policy responses to effectively manage the multifaceted challenges encountered by this vital link in the maize value chain.

REFERENCES

Anugwa, I.Q., E.A.R Obossou, R. Onyeneke, and J.M. Chah. 2023. "Gender perspectives in vulnerability of Nigeria's agriculture to climate change impacts: a systematic review." *GeoJournal* 88(1):1139-1155.

Bazzani, C., G.W. Gustavsen, R.M. Nayga Jr, and K. Rickertsen. 2018. "A comparative study of food values between the United States and Norway." *European Review of Agricultural Economics* 45(2):239-272.

Bhat, C.R. 2001. "Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model." *Transportation Research Part B: Methodological* 35(7):677-693.

Brechenmacher, S. 2019. "Stabilizing Northeast Nigeria After Boko Haram." Working paper, Carnegie Endowment for International Peace.

Caputo, V., and J.L. Lusk. 2019. "What Agricultural and Food Policies Do US Consumer Prefer? A Best-Worst Scaling Approach." *Agricultural Economics* 51:75-93.

Costanigro, M., C. Appleby, and S.D. Menke. 2013. "The Wine Headache: Consumer Perceptions of Sulfites and Willingness to Pay for Non-Sulfited Wines." *Food Quality and Preference* 31:81-89.

Finn, A., and J.J. Louviere. 1992. "Determining the Appropriate Response to Evidence of Public Concern: The Case of Food Safety." *Journal of Public Policy and Marketing* 11:12-25.

Hickle, J. 2020. "Domestic Resource Mobilization and Economic Recovery in Africa." Open Government Partnership.

International Republican Institute (IRI) and National Democratic Institute (NDI). 2019. "IRI/NDI Nigeria International Election Observation Mission Final Report".

International Rescue Committee. 2016. *Nigeria: Strategy Action Plan*.

Isola, A.A., and A. Tolulope. 2022. "Women, security, and gender-based violence in the northeast, Nigeria." *Journal of International Women's Studies* 24(4): Article 6.

Jaffee, S., P. Siegel, and C. Andrews. 2010. "Rapid agricultural supply chain risk assessment: A conceptual framework." *Agriculture and rural development discussion paper* 47(1):1-64.

Jarrett, R.G., and W.B. Hall. 1978. "Generalized cyclic incomplete block designs." *Biometrika* 65(2):397-401.

John, J.A. 1981. "Efficient Cyclic Designs." *Journal of the Royal Statistical Society* 43(1):76-80.

Krinsky, I., and A.L. Robb. 1986. "On approximating the statistical properties of elasticities." *Review of Economics and Statistics* 64:715-719.

Lawson, J. 2014. Design and Analysis of Experiments with R. Vol. 115. CRC press.

Lister, G., G.T. Tonsor, M. Brix, T.C. Schroeder, and C. Yang. 2017. "Food values applied to livestock products." *Journal of Food Products Marketing* 23(3):326-341.

Liverpool-Tasie, S., T. Reardon, A. Sanou, W. Ogunleye, I. Ogunbayo, and B.T. Omonona. 2017. "*The transformation of value chains in Africa: Evidence from the first large survey of maize traders in Nigeria*." Research Paper 91, Feed the Future Innovation Lab for Food Security Policy, Michigan State University.

Louviere, J.J., T.N. Flynn, and A.A.J. Marley. 2015. *Best-worst scaling: Theory, methods and applications*. Cambridge University Press.

Lusk, J.L., and B.C. Briggeman. 2009. "Food Values." *American Journal of Agricultural Economics* 91:184-196.

Maredia, M.K., J. Goeb, D.L. Ortega, N.L.K. Synt, and A.M. Zu. 2022. "Preferences for pandemic recovery policies: Perspectives of Myanmar agri-food system participants." *Journal of the Agricultural and Applied Economics Association* 1(3):334-351.

Mason, N.M., A. Kuteya, D. Resnick, V. Caputo, M. Maredia, R. Shupp, and H. Ngoma. 2019. "Smallholder farmers' and other agricultural sector stakeholders' priorities for government spending: Evidence from Zambia." Research Paper 155, Feed the Future Innovation Lab for Food Security Policy, Michigan State University.

McFadden, D. 1974. "Conditional logit analysis of qualitative choice behavior." In P. Zarembka, ed. *Frontiers in econometrics*. New York: Academic Press, pp.105-142.

McKendree, M.G.S., G. Tonsor, and C.A. Wolf. 2018. "Animal welfare perceptions of the US public and cow-calf producers." *Journal of Agricultural and Applied Economics*, 50(4):544-578.

Mogues, T., M. Morris, L. Freinkman, A. Adubi, and S. Ehui. 2008. "Agricultural public spending in Nigeria." Discussion Paper 00789, International Food Policy Research Institute.

Mogues, T., and T. Olofinbiyi. 2016. "Institutions and Public Agricultural Investments: A Qualitative Study of State and Local Government Spending in Nigeria." Working Paper 37, International Food Policy Research Institute.

National Bureau of Statistics. 2019. LSMS Integrated Surveys on Agriculture Nigeria General Household Survey-Panel Wave 4.

National Social Safety Net Coordinating Office (NASSCO). 2015. "Nigeria: Social Protection Status Report."

Nigeria Federal Ministry of Environment, Department of Climate Change. *National Climate Change Policy for Nigeria 2021-2030*.

Nogales, R., and C. Oldiges. 2023. "Multidimensional poverty and conflict events in Nigeria over time." *International Political Science Review* 01925121231177441.

Ojo, J.S., S. Oyewole, and F. Aina. 2023. "Forces of terror: Armed banditry and insecurity in North-west Nigeria." *Democracy and Security* 1-28.

Ola, O., and L. Menapace. 2020. "Revisiting constraints to smallholder participation in high-value markets: A best-worst scaling approach." *Agricultural Economics* 51(4):595-608.

Ortega, D.L., S. Hong, N.J.O Widmar, H.H. Wang, and L. Wu. 2015. "Chinese Aquaculture Farmers' Value System and On-Farm Decision Making." *International Journal of Agricultural Management* 4(3):93-99.

Papke, L.E., and J.M. Wooldridge. 1996. "Econometric methods for fractional response variables with an application to 401(k) plan participation rates." *Journal of Applied Econometrics* 11(6): 619-632.

Stone, J., M. Costanigro, and C. Goemans. 2018. "Public Opinion on Colorado Water Rights Transfers: Are Policy Preferences Consistent with Concerns Over Impacts?" *Journal of Agricultural and Resource Economics* 43(3):403-22.

Train, K. 2009. *Discrete choice methods with simulation*. Cambridge, UK: Cambridge University Press.

Umberger, W.J., T. Reardon, R. Stringer, and S.M. Loose. 2015. "Market-Channel Choices of Indonesian Potato Farmers: A Best-Worst Scaling Experiment." *Bulletin of Indonesian Economic Studies* 51(3):461-477.

Uwaoma Ugochukwu, G.A., C.O. Esi-Ubani, and E.P. Chinenye. 2018. "Warehousing Management Systems and Sales of Maize in Abia State, Nigeria." *International Journal of Social Science and Humanities* Research 6(2):230-239.

U.S. Department of Agriculture (USDA). 2019. *Nigeria Animal Feed Sector Snapshot – 2019*. GAIN Report No. NG-19005, Washington DC, May.

Vargas, C.M., T. Reardon, and L.S.O. Liverpool-Tasie. 2023. "Confluence of climate, violence, disease, and cost shocks: vulnerability of and impacts on Nigerian Maize Traders." Department of Agricultural, Food, and Resource Economics Staff Paper Series #2023-002, Michigan State University, August.

Wolf, C.A., and G.T. Tonsor. 2013. "Dairy Farmer Policy Preferences." *Journal of Agricultural and Resource Economics* 38(2):220-234.

APPENDIX

Table A.1 Correlated RPL results for conflict shock policies – by gender

		Female Traders			Male Traders		
	Conflict shock policies	Mean	Std. Dev.	Share of preferences	Mean	Std. Dev.	Share of preferences
Soft	Cash relief	2.481***	1.909***	26.1	2.520***	0.252***	34.4
		(0.194)	(0.227)	(0.027)	(0.091)	(0.093)	(0.015)
	Call center - **BASE**	0.000	-	2.2	0.000	-	2.8
				(0.003)			(0.002)
	Training	0.160	0.641***	2.6	0.435***	0.502***	4.3
		(0.157)	(0.145)	(0.004)	(0.075)	(0.064)	(0.003)
	Road security	2.240***	0.962***	20.5	1.850***	1.109***	17.6
		(0.188)	(0.160)	(0.024)	(0.084)	(0.080)	(0.009)
	Insurance	1.145***	2.117***	6.9	0.403***	1.521***	4.1
		(0.191)	(0.151)	(0.010)	(0.083)	(0.066)	(0.003)
	Loans	-0.047	0.517***	2.1	0.437***	0.963***	4.3
		(0.176)	(0.177)	(0.003)	(0.081)	(0.067)	(0.003)
	Market/warehouse security	2.384***	1.086***	23.7	1.746***	0.872***	15.9
		(0.194)	(0.210)	(0.025)	(0.083)	(0.075)	(0.008)
Hard	Market/warehouse infrastructure	1.467***	1.575***	9.5	1.385***	0.676***	11.1
		(0.182)	(0.232)	(0.011)	(0.081)	(0.078)	(0.006)
	Market/warehouse energy	1.076***	1.369***	6.4	0.683***	0.799***	5.5
		(0.174)	(0.212)	(0.008)	(0.079)	(0.075)	(0.003)
	Sum of share of preferences			100%			100%
	Number of traders		59			232	
	N		531			2,088	
	LLF		-935.544			-4,021.184	
	AIC / N		3.689			3.894	
	BIC / N		4.044			4.013	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Table A.2 Correlated RPL results for weather shock policies – by gender

		Female Traders			Male Traders		
	Weather shock policies	Mean	Std. Dev.	Share of preferences	Mean	Std. Dev.	Share of preferences
Soft	Cash relief	1.822***	0.445**	24.3	2.268***	0.055	33.7
		(0.171)	(0.184)	(0.024)	(0.088)	(0.090)	(0.015)
	Loans	0.192	1.600***	4.7	0.438***	0.637***	5.4
		(0.155)	(0.175)	(0.006)	(0.074)	(0.078)	(0.003)
	Insurance	0.362**	1.443***	5.6	-0.016	1.107***	3.4
		(0.162)	(0.145)	(0.008)	(0.075)	(0.067)	(0.002)
	Call center - **BASE**	0.000	-	3.9	0.000	-	3.5
				(0.005)			(0.002)
	Training	0.026	1.238***	4.0	0.095	0.378***	3.8
		(0.157)	(0.168)	(0.006)	(0.074)	(0.064)	(0.003)
Hard	Road infrastructure	2.223***	1.987***	36.2	2.102***	1.299***	28.5
		(0.196)	(0.158)	(0.034)	(0.090)	(0.074)	(0.014)
	Market/warehouse infrastructure	1.420***	0.914***	16.2	1.614***	1.062***	17.5
		(0.166)	(0.128)	(0.017)	(0.085)	(0.068)	(0.010)
	Market/warehouse energy	0.246	1.563***	5.0	0.184**	0.514***	4.2
		(0.162)	(0.182)	(0.007)	(0.077)	(0.066)	(0.003)
	Sum of share of preferences			100%			100%
	Number of traders		59			232	
	N		472			1,856	
	LLF		-911.803			-3,628.564	
	AIC / N		4.012			3.948	
	BIC / N		4.320			4.052	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Table A.3 Correlated RPL results for conflict shock policies – by scale

		Large Traders			Small Traders		
	Conflict shock policies	Mean	Std. Dev.	Share of preferences	Mean	Std. Dev.	Share of preferences
Soft	Cash relief	2.546***	0.604***	32.3	2.474***	1.231***	33.5
		(0.111)	(0.125)	(0.017)	(0.125)	(0.140)	(0.021)
	Call center - **BASE**	0.000	-	2.5	0.000	-	2.8
				(0.002)			(0.003)
	Training	0.453***	0.431***	4.0	0.431***	0.273***	4.3
		(0.093)	(0.078)	(0.003)	(0.098)	(0.090)	(0.004)
	Road security	1.807***	0.947***	15.4	1.893***	0.511***	18.7
		(0.104)	(0.073)	(0.010)	(0.111)	(0.086)	(0.013)
	Insurance	0.998***	2.141***	6.9	0.227**	1.246***	3.5
		(0.105)	(0.105)	(0.005)	(0.108)	(0.089)	(0.003)
	Loans	0.586***	0.938***	4.6	0.135	0.739***	3.2
		(0.102)	(0.075)	(0.004)	(0.107)	(0.079)	(0.003)
	Market/warehouse security	1.920***	0.867***	17.3	1.831***	0.863***	17.6
		(0.106)	(0.087)	(0.011)	(0.111)	(0.096)	(0.012)
Hard	Market/warehouse infrastructure	1.632***	0.671***	12.9	1.220***	0.736***	9.5
		(0.104)	(0.095)	(0.008)	(0.107)	(0.106)	(0.007)
	Market/warehouse energy	0.484***	0.646***	4.1	0.870***	0.490***	6.7
		(0.099)	(0.094)	(0.003)	(0.104)	(0.101)	(0.005)
	Sum of share of preferences			100%			100%
	Number of traders		159			132	
	N		1,431			1,188	
	LLF		-2,759.743			-2,293.015	
	AIC / N		3.919			3.934	
	BIC / N		4.080			4.123	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Table A.4 Correlated RPL results for weather shock policies – by scale

		Large Traders			Small Traders		
	Weather shock policies	Mean	Std. Dev.	Share of preferences	Mean	Std. Dev.	Share of preferences
Soft	Cash relief	2.296***	0.613***	32.8	2.069***	0.843***	36.0
		(0.111)	(0.118)	(0.018)	(0.115)	(0.117)	(0.020)
	Loans	0.278***	0.627***	4.4	0.330***	0.837***	6.3
		(0.089)	(0.102)	(0.004)	(0.097)	(0.097)	(0.005)
	Insurance	0.552***	1.460***	5.7	-0.229**	0.924***	3.6
		(0.095)	(0.091)	(0.005)	(0.099)	(0.089)	(0.003)
	Call center - **BASE**	0.000	-	3.3	0.000	-	4.5
				(0.003)			(0.004)
	Training	0.103	0.267***	3.7	0.121	0.409***	5.1
		(0.090)	(0.100)	(0.003)	(0.099)	(0.093)	(0.004)
Hard	Road infrastructure	2.201***	1.558***	29.8	1.668***	1.456***	24.1
		(0.108)	(0.105)	(0.017)	(0.111)	(0.087)	(0.016)
	Market/warehouse infrastructure	1.623***	1.220***	16.7	1.152***	0.983***	14.4
		(0.102)	(0.100)	(0.011)	(0.103)	(0.082)	(0.010)
	Market/warehouse energy	0.074	0.593***	3.6	0.253**	0.352***	5.9
		(0.096)	(0.109)	(0.003)	(0.101)	(0.099)	(0.005)
	Sum of share of preferences			100%			100%
	Number of traders		159			132	
	N		1,272			1,056	
	LLF		-2,444.669			-2,093.846	
	AIC / N		3.899			4.032	
	BIC / N		4.041			4.196	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Table A.5 Correlated RPL results for conflict shock policies – by region

		Northern Traders			Southern Traders		
	Conflict shock policies	Mean	Std. Dev.	Share of preferences	Mean	Std. Dev.	Share of preferences
Soft	Cash relief	2.578***	0.053	34.9	2.046***	4.500***	21.6
		(0.090)	(0.093)	(0.015)	(0.202)	(0.392)	(0.030)
	Call center - **BASE**	0.000	-	2.7	0.000	-	2.8
				(0.002)			(0.004)
	Training	0.453***	0.364***	4.2	-0.087	0.465***	2.6
		(0.073)	(0.069)	(0.003)	(0.167)	(0.125)	(0.004)
	Road security	1.762***	0.740***	15.5	2.242***	1.182***	26.3
		(0.081)	(0.064)	(0.008)	(0.194)	(0.160)	(0.028)
	Insurance	0.560***	1.477***	4.6	0.429**	1.701***	4.3
		(0.081)	(0.067)	(0.03)	(0.183)	(0.226)	(0.006)
	Loans	0.393***	0.842***	3.9	-0.271	1.194***	2.1
		(0.079)	(0.058)	(0.003)	(0.185)	(0.163)	(0.003)
	Market/warehouse security	1.858***	0.808***	17.0	1.900***	0.784***	18.7
		(0.082)	(0.069)	(0.008)	(0.191)	(0.162)	(0.023)
Hard	Market/warehouse infrastructure	1.610***	0.659***	13.3	0.295*	0.106	3.7
		(0.082)	(0.079)	(0.007)	(0.176)	(0.170)	(0.005)
	Market/warehouse energy	0.392***	0.712***	3.9	1.863***	0.400	18.0
		(0.078)	(0.068)	(0.003)	(0.191)	(0.249)	(0.021)
	Sum of share of preferences			100%			100%
	Number of traders		240			60	
	N		2,160			540	
	LLF		-4,105.354			-919.689	
	AIC / N		3.842			3.569	
	BIC / N		3.958			3.919	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Table A.6 Correlated RPL results for weather shock policies – by region

		Northern Traders			Southern Traders		
	Weather shock policies	Mean	Std. Dev.	Share of preferences	Mean	Std. Dev.	Share of preferences
Soft	Cash relief	2.332***	0.016	32.6	3.516***	3.164***	69.6
		(0.090)	(0.095)	(0.014)	(0.291)	(0.316)	(0.052)
	Loans	0.296***	0.869***	4.3	0.043	0.694***	2.2
		(0.075)	(0.081)	(0.003)	(0.153)	(0.163)	(0.005)
	Insurance	0.387***	1.191***	4.7	0.088	1.039***	2.3
		(0.077)	(0.068)	(0.003)	(0.157)	(0.161)	(0.005)
	Call center - **BASE**	0.000	-	3.2	0.000	-	2.1
				(0.002)			(0.005)
	Training	0.092	0.525***	3.5	0.144	0.702***	2.4
		(0.075)	(0.070)	(0.002)	(0.162)	(0.146)	(0.005)
Hard	Road infrastructure	2.235***	1.256***	29.6	1.700***	1.611***	11.3
		(0.090)	(0.076)	(0.013)	(0.181)	(0.144)	(0.021)
	Market/warehouse infrastructure	1.797***	0.910***	19.1	0.828***	1.353***	4.7
		(0.086)	(0.074)	(0.010)	(0.164)	(0.132)	(0.010)
	Market/warehouse energy	-0.034	0.620***	3.1	0.963***	1.033***	5.4
		(0.079)	(0.077)	(0.002)	(0.171)	(0.143)	(0.011)
	Sum of share of preferences			100%			100%
	Number of traders	240			60		
	N	1,920			480		
	LLF	-3,639.036			-911.793		
	AIC / N	3.827			3.945		
	BIC / N	3.928			4.249		

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Table A.7 Correlated RPL results for conflict shock policies – by education

		Traders with formal education			Traders without formal education		
	Conflict shock policies	Mean	Std. Dev.	Share of preferences	Mean	Std. Dev.	Share of preferences
Soft	Cash relief	2.059***	0.847***	27.6	3.330***	0.056	47.9
		(0.094)	(0.104)	(0.014)	(0.161)	(0.159)	(0.031)
	Call center - **BASE**	0.000	-	3.5	0.000	-	1.7
				(0.002)			(0.002)
	Training	0.418***	0.405***	5.4	0.378***	0.479***	2.5
		(0.081)	(0.062)	(0.003)	(0.121)	(0.112)	(0.003)
	Road security	1.621***	0.627***	17.8	2.154***	0.840***	14.8
		(0.088)	(0.073)	(0.009)	(0.141)	(0.108)	(0.014)
	Insurance	0.463***	1.260***	5.6	0.430***	1.355***	2.6
		(0.088)	(0.082)	(0.004)	(0.134)	(0.138)	(0.003)
	Loans	0.285***	0.768***	4.7	0.752***	1.708***	3.6
		(0.087)	(0.062)	(0.003)	(0.138)	(0.104)	(0.004)
	Market/warehouse security	1.597***	0.645***	17.4	1.952***	1.086***	12.1
		(0.088)	(0.069)	(0.009)	(0.141)	(0.114)	(0.012)
Hard	Market/warehouse infrastructure	1.127***	0.668***	10.9	1.842***	0.560***	10.8
		(0.087)	(0.078)	(0.006)	(0.134)	(0.132)	(0.011)
	Market/warehouse energy	0.705***	0.758***	7.1	0.816***	0.476***	3.9
		(0.085)	(0.074)	(0.004)	(0.127)	(0.132)	(0.004)
	Sum of share of preferences			100%			100%
	Number of traders		190			101	
	N		1,710			909	
	LLF		-3,444.687			-1,622.942	
	AIC / N		4.080			3.668	
	BIC / N		4.220			3.901	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Table A.8 Correlated RPL results for weather shock policies – by education

		Traders with formal education			Traders without formal education		
	Weather shock policies	Mean	Std. Dev.	Share of preferences	Mean	Std. Dev.	Share of preferences
Soft	Cash relief	1.877***	0.392***	28.9	2.873***	0.064	46.8
		(0.094)	(0.099)	(0.014)	(0.158)	(0.151)	(0.028)
	Loans	0.617***	1.112***	8.2	0.006	1.078***	2.7
		(0.085)	(0.084)	(0.005)	(0.122)	(0.118)	(0.003)
	Insurance	0.128	1.257***	5.0	0.177	1.169***	3.2
		(0.085)	(0.075)	(0.003)	(0.122)	(0.103)	(0.004)
	Call center - **BASE**	0.000	-	4.4	0.000	-	2.6
				(0.003)			(0.003)
	Training	0.245***	0.667***	5.7	-0.146	0.854***	2.3
		(0.083)	(0.079)	(0.004)	(0.125)	(0.112)	(0.003)
Hard	Road infrastructure	1.814***	1.142***	27.1	2.187***	1.176***	23.6
		(0.093)	(0.074)	(0.014)	(0.144)	(0.103)	(0.020)
	Market/warehouse infrastructure	1.245***	0.868***	15.4	1.796***	0.939***	15.9
		(0.087)	(0.070)	(0.009)	(0.137)	(0.099)	(0.015)
	Market/warehouse energy	0.178**	0.700***	5.2	0.139	0.840***	3.0
		(0.087)	(0.088)	(0.004)	(0.126)	(0.114)	(0.004)
	Sum of share of preferences			100%			100%
	Number of traders		190			101	
	N		1,520			808	
	LLF		-3,008.586			-1,478.678	
	AIC / N		4.005			3.747	
	BIC / N		4.127			3.950	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.

Table A.9 Correlated RPL results for conflict shock policies – by conflict shock experience

		Experienced conflict shock			Did not experience conflict shock		
	Conflict shock policies	Mean	Std. Dev.	Share of preferences	Mean	Std. Dev.	Share of preferences
Soft	Cash relief	2.638***	0.419*	34.3	2.311***	0.131	31.6
		(0.221)	(0.230)	(0.038)	(0.085)	(0.093)	(0.014)
	Call center - **BASE**	0.000	-	2.5	0.000	-	3.1
				(0.004)			(0.002)
	Training	0.703***	0.633***	5.0	0.338***	0.436***	4.4
		(0.184)	(0.144)	(0.008)	(0.074)	(0.071)	(0.003)
	Road security	2.194***	1.911***	22.0	1.669***	0.772***	16.6
		(0.213)	(0.156)	(0.029)	(0.080)	(0.071)	(0.008)
	Insurance	0.069	2.179***	2.6	0.553***	1.865***	5.4
		(0.234)	(0.199)	(0.005)	(0.085)	(0.092)	(0.004)
	Loans	0.868***	1.102***	5.8	0.348***	1.005***	4.4
		(0.201)	(0.157)	(0.009)	(0.080)	(0.069)	(0.003)
	Market/warehouse security	1.724***	1.418***	13.8	1.694***	0.582***	17.1
		(0.207)	(0.155)	(0.018)	(0.081)	(0.081)	(0.008)
Hard	Market/warehouse infrastructure	1.234***	0.365**	8.4	1.283***	0.529***	11.3
		(0.195)	(0.165)	(0.011)	(0.078)	(0.082)	(0.006)
	Market/warehouse energy	0.820***	1.699***	5.6	0.643***	0.494***	6.0
		(0.199)	(0.161)	(0.009)	(0.078)	(0.080)	(0.003)
	Sum of share of preferences			100%			100%
	Number of traders		45			246	
	N		405			2,214	
	LLF		-751.124			-4,322.961	
	AIC / N		3.927			3.945	
	BIC / N		4.362			4.058	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Share of preferences were computed using the Krinsky and Robb (1986) bootstrapping method.