Market Channel and Heterogeneous Storage Behavior in Response to Multiple Risks: The Case of Nigerian Maize Traders

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Selected Paper prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington DC; July 23-25, 2023

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Abstract

This study investigates the impacts of multiple risks induced by climate, armed conflicts, and spoilage of maize on the storage behavior of maize traders. We use data from a unique, large sample survey of Nigerian maize wholesale traders as representative actors in the midstream of the maize value chain. In addition to focusing on a segment of the value chain often ignored, we extend a triple-hurdle model to allow for an initial stage of traders' choice of their main market channel (i.e., between traditional and modern buyers). As different market channels are likely to have varying contract design and quality standards for the maize, traders may adjust their storage behaviors depending on their market channel. Thus, we first examine the effects of risks on traders' decision to store maize and adopt different damage control practices (e.g., applying chemicals and/or non-chemicals) on stored maize. Then we investigate how the effects of these risks vary by traders' main market channel. We find consistent evidence of heterogenous trader responses to risks depending on their main market channel. For example, temperature fluctuation affects the probability to store in opposite ways for traders selling to traditional buyers versus those selling to modern buyers. Additionally, previous experience with climate-induced shocks has no effect on the storage practices of traders selling to modern buyers but is positively associated with chemical use among traders selling to traditional buyers. This raises concerns about the safety of maize and highlights the importance of considering traders' market channel choice when developing policies for mitigating the impact of risks and building resilient maize value chains that can deliver safe and nutritious foods.

Keywords: Maize value chain, market channel, storage, maize traders, climate-induced shocks, conflicts, triple hurdle model

1. Introduction

Agrifood value chains in developing countries have rapidly expanded and transformed over the last few decades, largely driven by liberalization in trade, privatization of agricultural parastatals, urbanization, and growth in income (Muyanga et al., 2019; Reardon, 2015; Reardon, Liverpool-Tasie, and Minten, 2021). While such expansion and transformation has occurred across all segments of the value chains, the middle segment or midstream, including logistics, processing, and wholesaling, has received significantly less research and policy attention than the upstream and the downstream (Reardon, 2015). Midstream actors are vital because they act as intermediaries between upstream agrifood producers and downstream consumers, engaging in the long agrifood value chains (Abate et al., 2015; Reardon, 2015). According to Reardon et al. (2012), midstream actors' activities account for at least 30–40% of total value added in starchy food value chains.

Midstream actors of staple food value chains play a crucial role when an economy is heavily dependent on staple foods, as is the case in many developing countries. In Nigeria, for example, more than 70% of households engage in crop farming, and maize is the most commonly grown crop, with about 50% of farming households growing it (National Bureau of Statistics, 2019). Nigeria's maize production recently rose to the highest level since 1960, reaching above 12.7 million metric tons and making it the largest maize producer in Africa (USDA, 2022). Maize is also a key staple food and an important ingredient for animal feed in the country as more than 60% of the production is used for animal feed (USDA, 2019), reflecting recent changes in diets and increased consumption of animal products (Herrero et al., 2014). Among the midstream actors in the maize value chain, maize traders are the "funnel" via which maize is sold to the market. Furthermore, maize traders' storing of maize, controlling damage while it is stored, and transporting maize influence the safety, quality, and price of maize for consumers.

As maize value chains expand and lengthen (e.g., in geographical distance or number of actors or segments), they become subject to increasing risks. Understanding how different risks affect the value chains, particularly the midstream, is essential to build policies that mitigate the impacts of such risks. We focus on Nigerian maize traders as representative midstream actors and analyze their storage behaviors in response to multiple risks and past experience of shocks induced by climate change, armed conflicts, and spoilage of maize. Furthermore, we assess how the storage behaviors vary with traders' market channel choices between selling to "modern buyers" (industrial food and feed mills) versus "traditional buyers" such as consumers, other wholesalers, and retailers. Modern buyers are likely to require the maize to meet certain quality standards and buy higher-quality maize at higher prices compared to traditional buyers (Hoffmann and Moser, 2017; Sanou et al., 2021).[1] Hence, understanding traders' behaviors by their market channel is important as different traders would have varying incentives, which would lead to different responses to risks and policies addressing such risks.

Existing studies that have examined the midstream actors in developing countries' agrifood value chains have tended to assess the impact of only climate risk or conflict shocks (Hastings et al., 2022; Liverpool-Tasie and Parkhi, 2021). Most do not account for the effects of such events varying across traders depending on whom they primarily sell to. This is the first study (that we are aware of) to examine the impact of multiple risks at the same time (i.e., climate-, spoilage-, and conflict-induced risks) on maize traders' storage behaviors by market channel choice. We first examine the extent to which these different risks affect the decision to

[1] It is widely known that desired attributes lead to price premium (Gómez et al., 2011; Vandeplas, Minten, and Swinnen, 2009).

store and then particular storage behaviors for traders who store. In both sets of decisions, we explore how the impact of risks varies by their main market channel choice.

Considerable research attention has been given to examining traders and their behavior in developing countries. With the movement toward market liberalization and governments disengaging or scaling down their involvement in agricultural marketing, private traders started to enter the market. Consequently, the competitiveness of traders, or the level of competition among them, has been of great interest (Dillon and Dambro, 2017). While a large number of traders entered the market with reduced transaction costs as they could operate openly, some still faced barriers and risks in entering the market. In addition, not all markets with many traders were competitive (Barrett, 1997; Dillon and Dambro, 2017; Staatz, Dioné, and Dembele, 1989). Some research focused on spatial price differentials and market integration to determine whether traders behave competitively (Barrett, 1996; Dercon, 1995; Ravallion, 1986). Others focused on the cost and margins of traders' activities (Dessalegn, Jayne, and Shaffer, 1998; Fafchamps, Gabre-Madhin, and Minten, 2005; Gabre-Madhin, 2001). The risk that was identified as hindering traders from entering the market or altering traders' profit was mainly policy or regulatory uncertainty (Berg, 1989; Staatz, Dioné, and Dembele, 1989).

Minten and Kyle (1999) identified transportation costs and transaction costs as the two major factors that determine traders' margins. They showed that poor road infrastructure poses a significant risk and is a major source of the two costs, leading to price dispersion across markets. More recently, studies have examined the impacts of climate-induced risks on traders' profit (Arku, Angmor, and Adjei, 2017) and technology adoption behavior (Liverpool-Tasie and

Parkhi, 2021).[2] [3] Few studies, however, have investigated how spoilage and conflict risks affect traders and their behavior. Grain traders bear the risk of the grain being spoiled between purchase and sale (Dillon and Dambro, 2017), and traders' activities are also adversely affected if conflicts are prevalent, disrupting the production system, transportation, and/or the markets (Hastings et al., 2022). Hastings et al. (2022) is an exception that explored the role of conflicts in price transmission and market integration in Somalia.[4] What remains unclear is how multiple risks, either current or experienced in the past, from climate change, spoilage, and conflicts affect traders' behavior, storing in particular, and how these effects differ.

Storage plays an important role in smoothing consumption and stabilizing prices by taking seasonal harvests and making them available over the lean season (Myers, 2013). With the growth of private sector trading, considerable research has focused on the efficiency of private sector storage and its effect on prices and production of commodities (Brennan, 2003; Myers, 2013; Williams and Wright, 1991; Wright and Williams, 1982). The primary factors identified to affect private sector storage decisions include price changes, interest rates, and elasticity of demand (Brennan, 2003; Knudsen and Nash, 1990). More recently, Liverpool-Tasie and Parkhi (2021) identified climate-induced risk as a factor that affects traders' decision on storage and damage control of stored maize.

One important factor that has been neglected in explaining traders' behavior, including their decision to store and prevent damage or spoilage of stored products, is the consideration of

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[2] Stokeld et al. (2020) found that traders with different sourcing profiles face different exposure to climate-induced risk. Adams et al. (2021) discuss the impact of climate risks in the context of international food trade.

[3] Previous studies on climate risks in developing countries have largely focused on farmers: the impact of climate risks on crop production (Haile et al., 2017; Jones and Thornton, 2003; Kabubo-Mariara and Mulwa, 2019; Müller et al., 2011); and farmers' adaptation to climate risks and/or the impact of adaptation on the production of food crops (Belay et al., 2017; Di Falco, Veronesi, and Yesuf, 2011; Holden and Quiggin, 2017).

[4] Conflicts have been widely discussed in the international trade literature (see, for example, Reuveny (2000)).

whom the traders sell to. On the other hand, market channel choice has been extensively discussed in the literature on farmers' decision-making. This includes studies on the factors affecting farmers' market channel choice (Arinloye et al., 2015; Negi et al., 2018; Xaba and Masuku, 2013) and the impact of farmers' market channel choice on household welfare (Mmbando, Wale, and Baiyegunhi, 2017), income (Zhang, Kagatsume, and Yu, 2014), profitability (Mehdi et al., 2019), and output prices and price stability (Michelson, Reardon, and Perez, 2012).

To our knowledge, this paper is the first to examine the impact of multiple risks – climate-, spoilage-, and conflict-induced risks – on maize traders' storage behaviors based on their market channel choice. Specifically, we examine the extent to which the risks influence storage behaviors and how the extent varies depending on whether traders mainly sell their maize through traditional or modern market channels. Similar to the research of Liverpool-Tasie and Parkhi (2021) on the effects of climate risk and perception on various value-adding technologies, including storage and damage control for stored maize, we also regard storage as a value-adding practice that is vulnerable to climate-, spoilage-, and conflict-induced risks. We use data from a unique and large sample survey of Nigerian maize traders and extend the traditional triple hurdle model of Burke, Myers, and Jayne (2015) to explore the effects of multiple risks on maize traders' decisions to: (i) select their main market channel – traditional buyers versus modern buyers; (ii) adopt maize storage (or not) conditional on their target market; and (iii) implement practices to control damage for stored maize (or not) conditional on who they sell to and storing maize.

This paper contributes to the literature in three ways. First, we contribute to the currently thin understanding of the behavior of actors in the midstream of agrifood value chains. Despite the key role played by the overall midstream sector and maize traders in developing countries, large sample datasets and studies to understand this underemphasized “hidden middle” are scant (Liverpool-Tasie et al., 2017; Reardon, Liverpool-Tasie, and Minten, 2021). We help to fill this gap by investigating Nigerian maize traders’ storage behaviors in the face of multiple risks. While Liverpool-Tasie and Parkhi (2021) assessed the impact on traders’ storage behavior of climate risk only, we assess the impact of climate-induced risk as well as traders’ past exposure to shocks incurred by climate, spoilage, and conflicts. Second, we add to the literature on market channel choice. While most research in the literature has focused on farmers’ market channel decisions, we consider maize traders’ decision between different market channels and demonstrate that market channel choice associates with the impact of risks on their storage behavior. Finally, we extend the triple-hurdle model of Burke, Myers, and Jayne (2015) to analyze the adoption decisions of storage and practices to prevent damage on storage (damage controlling) by maize traders selling to different market channels. While triple-hurdle models have been used in several studies in the technology adoption literature (Claytor, 2015; Duniya, 2018; Jensen et al., 2015), we allow for an initial stage of main market channel choice between traditional versus modern. Traders selling to each market channel both adopt storage but probably differently (Singbo et al., 2021). In addition, we apply a bivariate probit model in the third stage of a triple-hurdle model for the choice of two different practices to prevent damage: applying chemicals and/or non-chemicals on stored maize.

2. Theoretical Framework

Following the approach of Liverpool-Tasie and Parkhi (2021), we consider Nigerian maize traders as small and medium-scale enterprises whose objective is to maximize expected profit by purchasing maize, adding value to it (through storing maize and/or applying damage control practices on stored maize), and selling it. While we assume maize traders are price takers, it is known that maize with certain quality, such as meeting some food safety standards required by buyers or having less damage from pests, entails a quality premium reflected in higher prices (Hatzenbuehler, Abbott, and Abdoulaye, 2017; Hoffmann and Moser, 2017; Kadjo, Ricker-Gilbert, and Alexander, 2016). Adding value to maize through adopting storage and/or damage control practices is thus an important way to maximize profit. Traders can exploit price differences across different times by buying maize when the price is low, storing it, and selling it when the price is high. Conditional on storage, traders can adopt damage control practices to maintain the quality of maize at a certain level.

However, traders' activities, including buying, storing, and selling maize, entail risks and costs. First, climate-induced risks, such as extreme variability in rainfall and temperature in traders' business operation areas, can influence their ability to store and control the quality of stored maize (Liverpool-Tasie and Parkhi, 2021). This is because such variability could raise the possibility of pest and disease incidence in stored maize, which then affects the quantity, quality, and price of maize that traders can sell to buyers (Liverpool-Taise et al., 2019; Liverpool-Tasie and Parkhi, 2021; Stathers, Lamboll, and Mvumi, 2013; Suleiman, Rosentrater, and Bern, 2013; Tefera, 2012). The experience of climate-induced shocks, such as disruption in traders' ability to source maize due to floods and droughts in the production area, also affects their decision to store maize. Traders who experienced such disruptions in the past may tend to store more to secure maize. However, it is also plausible that traders store less because they were not able to source enough maize to store after selling to buyers. Second, experience of spoilage shocks in the past, such as an aflatoxin outbreak or pests and rodents affecting stored maize, is also an important factor that can alter traders' decisions on storing and applying chemicals and/or non-chemicals to prevent damage. Finally, conflict-induced shocks, such as having experienced difficulties in sourcing or selling maize due to Boko Haram or farmer-herder conflicts in Nigeria, can also affect Nigerian traders' storage decisions. The experience of such disruption may alter their decision to store maize or not and to apply damage control practices to secure maize.

Maize traders' expected profit consists of three parts: (i) revenue from selling just-purchased maize; (ii) expected revenue from selling stored maize in the future; and (ii) costs of buying maize and costs associated with storing and/or applying chemicals and non-chemicals to prevent damage in stored maize. Suppose a maize trader buys maize of total quantity Q_b at price p_b. The trader can adopt storage z, a value-adding practice that entails climate-, spoilage-, and conflict-induced risks, at cost p_z of renting or owning storage facilities each period. Let Q_z be the stored quantity of maize. Traders' (expected) selling price of maize is assumed to be a function of its quality and the time that has passed since traders purchased and stored maize. The probability of maize getting damaged is likely to increase as the storage time increases. We denote the market sales price of maize as $p_s^t(h, t)$, where h is maize quality and t indicates the t^{th} period after the purchase of maize ($t = 0$ when maize is sold at the time of purchase). The amount of grain stored, Q_z, also depends on current sales price, p_s^0.

Given that maize is stored ($z = 1$ or $Q_z > 0$), the quality of maize is largely determined by the adoption of damage control practices $\boldsymbol{x}$ to prevent spoilage from insect or rodent infestation and/or mold growth. There are two ways in controlling damages, $\boldsymbol{x} = (x_1, x_2)$, where x_1 indicates the application of chemicals such as fumigant, pesticide, and repellent and x_2 indicates the application of non-chemicals such a pepper, ash, hermitic bags, and traditional medicine. We denote the prices for applying chemicals and non-chemicals as a vector $\boldsymbol{p_x}$. Although there are food safety issues in applying chemicals since chemical residues in maize can cause serious health risks (Kadjo et al., 2020), both chemicals and non-chemicals can prevent damages in stored maize. We denote D as the damage control function, which is the share of stored maize that has not been damaged by the application of damage control practices (Lichtenberg and Zilberman, 1986). Hence, we express the damage control function as $D(\boldsymbol{x}, t)$, which increases in $\boldsymbol{x}$, decreases in t, and ranges between 0 and 1. The quantity of maize that a trader can sell in period t depends on the amount of stored maize as well as the damage control function, $Q_s^t\big(Q_z, D(\boldsymbol{x}, t)\big)$, which is non-decreasing in D. The quality of maize also depends on damage controlling, thus $h(D(\boldsymbol{x}, t))$. In addition, we assume that traders decide whether to store maize or sell it right away when they purchase maize; if they decide to store, they store all of the purchased maize; and they sell all of the stored maize at time t.

Factors of primary interest in shaping maize traders' adoption of storage and damage control practices are the various risks and traders' market channel choice. Risks are introduced as a vector $\boldsymbol{k}$ that consists of: (i) current climate risks, including variability in rainfall and temperature in traders' business area between April and July 2021, which is right before traders make storage decisions; (ii) experience of climate-induced shocks; (iii) experience of spoilage shocks; and (iv) experience of conflict-induced shocks in the past year, from August 2020 to July 2021. As previously discussed, such events could disrupt traders' ability to secure and store maize and control damages in stored maize, which, in turn, affect the quality and price of maize available for sale. We further assume that maize traders face different *effective* sales price depending on their market channel choice. The price premium from meeting the market channel's quality standards, as well as the extra costs, such as the costs of drying maize or testing the quality of maize, are assumed to be incorporated into the effective price. Thus, the effective price of selling to market channel j is expressed as $p_s^t(h, t, \boldsymbol{k}; j)$. In addition, traders would have different underlying characteristics, represented by exogenous variables $\boldsymbol{v}$, which would mainly affect the effectiveness of damage controlling, $D(\boldsymbol{x}, t, \boldsymbol{k}; \boldsymbol{v})$. Hence, traders' expectation on the market price can be expressed as:

$$E(p_s^t; j) = E\left[p_s^t\left(h\left(D(\boldsymbol{x}, t, \boldsymbol{k}; \boldsymbol{v})\right), t, \boldsymbol{k}, p_s^0; j\right)\right] \quad (1)$$

which also depends on the current market price.

The expected profit from selling maize to market channel j is:

$$E\left(\pi^j\right) = p_s^0(h; j) * (Q_b - Q_z)$$
$$+E\left[p_s^t\left(h\left(D(\boldsymbol{x}, t, \boldsymbol{k}; \boldsymbol{v})\right), t, \boldsymbol{k}, p_s^0; j\right)\right] * E\left[Q_s^t\left(Q_z, D(\boldsymbol{x}, t, \boldsymbol{k}; \boldsymbol{v})\right)\right]$$
$$-(p_b * Q_b + p_z * Q_z * t + \boldsymbol{p_x} * \boldsymbol{x} * Q_z) \quad (2)$$

We assume that traders compare $E\left(\pi^j\right)$ for the two market channels j=modern and traditional and sell to the channel that yields higher expected profit, given $\boldsymbol{v}$.

The expected profit maximization problem provides a set of decision rules for the demand of storing and adopting damage control practices conditional on storing at time t:

$$Q_z^j(t) = z^j(E(p_s^t), p_s^0, \boldsymbol{p_x}, p_z, p_b, E(\boldsymbol{k}), \boldsymbol{v}) \quad (3)$$

$$\boldsymbol{x}^j(t) = \boldsymbol{x}^j(E(p_s^t), p_s^0, \boldsymbol{p_x}, p_z, p_b, E(\boldsymbol{k}), \boldsymbol{v}) \text{ when } Q_z^j(t) > 0 \quad (4)$$

3. Data

We utilize a survey of maize wholesale traders conducted in late 2021, which covers the major grain markets in Nigeria. The states covered include Kano, Kaduna, Katsina, and Plateau, which are the primary maize producing states in northern Nigeria, and Oyo in southern Nigeria, which is a major maize consuming area (where some maize production occurs). In each state, the main city was selected, and all maize markets within each city were listed.[5] All maize traders in each city maize market were then listed and interviewed.[6] In addition, all regional markets in the four northern states that serve other states in Nigeria or other countries were listed. The listing of all regional markets in the four northern states resulted in a total of 5,929 maize traders across 61 markets.

The traders were stratified into two groups: 'large trader stratum' with maize sales above 32 tons during a typical month in the high maize trading season, and 'small trader stratum' with maize sales below 32 tons during the same period. The top five regional markets with high total maize volume were selected in each of the northern states, and in each of the chosen regional markets, 30 traders were randomly selected: 15 from the large trader stratum and 15 from the small trader stratum. As a result, our study sample included 1,109 traders, with 584 traders from Kano, 136 traders from Kaduna, 170 traders from Katsina, 137 traders from Plateau, and 80 traders from Oyo.[7]

The survey collected detailed information including maize traders' demographic characteristics, assets, maize purchases and sales, value adding, and business environment shocks and their responses to the shocks. Purchase and sales, or trading activities, were surveyed for the high trading season (August 2020 – February 2021), low trading season (March 2021 – July 2021), and the last transactions (the last batch of maize traders sold before the survey). In addition, we obtained rainfall and temperature data at the local government level from the

[5] The main cities selected were Kano City in the Kano state; Kaduna in the Kaduna state; Katsina in the Katsina state; Jos in the Plateau state; and Ibadan in the Oyo state.
[6] A total of 903 wholesalers across 23 city markets were listed. However, only 822 wholesalers were eventually interviewed due to non-response.
[7] Two traders' location information (including the state they operate) is missing.

Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) and Climate Data Store (CDS), respectively, and linked them to the location of traders.

Table 1 presents the variables used in the analysis along with their summary statistics. The dependent variables include traders' storage behaviors and main market channel choice. Information on storage behaviors was collected only for the last transaction. Among the traders in the survey, 64% stored maize during the last transaction. Among those who stored maize, 20% applied chemicals and 5% applied non-chemicals on stored maize to prevent damage.

Traders engage in selling maize to various market channels, including consumers, other wholesalers, retailers, processors, and other entities. Processors mainly consists of feed mills and flour mills or the food industry, while the others include governmental and non-governmental organizations, albeit representing a minority.[8] We classified the five market channels into two main channels: modern and traditional. The modern market channel encompasses processors and the others, which have emerged more recently as formal market channels. In contrast, the traditional market channel encompasses consumers, other wholesalers, and retailers. Given that traders usually sell to multiple market channels, we determined their "main" channel based on the percentage of maize sold to each of the five channels during the high trading season and then constructed the binary market channel variable.[9]

The risks that traders face in the maize market consist of climate-induced risks and shocks experienced in the past. The coefficient of variations of monthly rainfall and temperature are included as indicators of variability in rainfall and temperature. They were computed using

[8] There are only 7 traders in total who mainly sold to "others".

[9] When there was a tie in the % of maize sold to each channel so that the main buyer could not be determined, we moved on to the % of maize sold to each channel in the low trading season. When there was a tie in the low season as well, we moved on to traders' last transaction. Market channel could not be determined for 52 traders since they had multiple main buyers even for the last transaction.

monthly data on rainfall and temperature in traders' business area during the growing season (April – July 2021), which was just before most traders stored maize (if they stored). The experience of climate-associated shocks was constructed based on the traders' response to whether they had encountered any of the following problems: maize shortage due to production disruptions caused by flood; maize shortage due to production disruptions caused by drought; significant delay in receiving maize due to roads washout; and washout or flood in the market destination area. The experience of spoilage shocks was constructed based on the traders' response to whether they had encountered any of the following issues: aflatoxin outbreak; pests affecting stored maize; rodents affecting stored maize; and serious spoilage of maize, for example, due to mold. Finally, the experience of conflict-related shocks was constructed based on the traders' response to whether they had encountered any of the following challenges: Boko Haram conflict in the North that directly affected their ability to sell maize; ability to buy maize from farmers; ability to buy maize from other traders; farmer-herder conflict affecting their ability to buy maize from farmers; and other insecurity problems such as banditry or kidnapping that impacted their ability to trade maize.

Summary statistics on the explanatory variables reveal that 88% of the traders are male and 71% are formally educated, that is, completed either primary, secondary, or university education. The average trading experience of the traders is around 20 years. Only a few traders received government or non-government training on maize storage techniques between August 2020 and July 2021, or government training on storage techniques in the past when they entered the trading business. Well above half of the traders are operating at a large scale (64%), with sales exceeding 32 tons per month during the peak season, and are members of a trader association (56%). Moreover, 14% of the traders engaged in other income-generating activities.

Distance to the highway is included as a proxy for traders' market access. The missing observations for the scale and price variables can be proxied by the volume of sales in the low season or the last transactions, and mean or median price in the traders' region, respectively.

Table 1. Definition of variables and summary statistics

Variable	Construction	Obs.	Mean	Std. Dev.
Dependent variables				
Storage	1 if trader stored maize during the last transaction, 0 else	1,109	.64	.48
Chemical	1 if applied chemical on stored maize to prevent damage, 0 else	711	.20	.40
Nonchemical	1 if applied non-chemical on stored maize to prevent damage, 0 else	711	.05	.22
Main market channel	1 if mainly sold to modern channel, 0 if mainly sold to traditional channel	1,057	.23	.42
*Risks (**k**)*				
CV of rainfall	Coefficient of variation of monthly rainfall (mm) between 4/2021-7/2021	1,107	.94	.34
CV of temperature	Coefficient of variation of monthly temperature (°C) between 4/2021-7/2021	1,107	.11	.02
Past climate shock	1 if experienced climate-induced shocks between 8/2020-7/2021, 0 else	1,109	.13	.34
Past spoilage shock	1 if experienced spoilage shocks between 8/2020-7/2021, 0 else	1,109	.03	.17
Past conflict shock	1 if experienced conflict-induced shocks between 8/2020-7/2021, 0 else	1,109	.49	.5
Explanatory variables ($\boldsymbol{v}$)				
Male	Trader's gender, 1 if male, 0 else	1,109	.88	.33
Education	1 if formally educated, 0 else	1,109	.71	.45
Years of trading	Number of years trader has been a maize wholesaler	1,098	20.00	8.74
Storage training	1 if has ever received storage technique training, 0 else	1,109	.02	.13
Scale	1 if has large monthly sales over 32 tons in the high season, 0 else	961	.64	.48
Distance to highway	Km distance from trader's business to the nearest highway	1,024	4.84	9.01
Trader association	1 if a member an organization/group associated with maize business, 0 else	1,109	.56	.50
Other job	1 if engaged in other income-generating jobs between 8/2020-7/2021, 0 else	1,109	.14	.35
Prices (p)				
Price	Sales price of maize for the last transactions (Naira/ton)	988	196,626.31	108,323.95

4. Empirical Model and Estimation

Market participation or technology adoption has been considered as a two-stage process that entails the decision of (i) whether to participate or adopt in the first stage, and (ii) the intensity or extent of participation or adoption in the second stage (Bellemare and Barrett, 2006; Goetz, 1992). Recently, Burke, Myers, and Jayne (2015) introduced a three-stage approach, namely the triple-hurdle model, to address the potential heterogeneity in the population of interest. In our study of maize traders, a double-hurdle approach for the adoption of storage would have been suitable if all maize traders in the sample primarily sold to the same market channel, either the modern or traditional channel. However, since maize traders sell to different market channels, storage decisions and the effect of multiple risks on storage decisions may vary across traders selling to different market channels. Hence, we employ a triple-hurdle model, extending the model proposed by Burke, Myers, and Jayne (2015), whose three stages consist of: (i) the decision to produce a particular commodity; (ii) the decision to participate in that commodity market, conditional on producing it; and (iii) the decision on the intensity of buying or selling, conditional on participation. Probit, ordered probit, and two log-normal models were applied in each stage.

Figure 1 illustrates the triple-hurdle approach employed in this paper. In the first stage, traders decide whether to primarily sell to modern or traditional market channel, and we apply a probit model to represent this decision. In the second stage, both traders selling to each market channel decide whether to store or not, represented by a probit model. Finally, in the third stage, traders who sell to the traditional channel decide whether to adopt chemicals and/or non-chemicals, conditional on storage. As traders can adopt both chemicals and non-chemicals at the same time, we apply a bivariate probit model to simultaneously estimate the likelihood of applying these treatments (Crick et al., 2018). However, for traders who sell mainly to the modern channel, we assume that they decide whether to apply any damage control treatment (either chemicals or non-chemicals) or not, and we apply a probit model. This is because we have insufficient observations of traders who sell mainly to the modern channel and store, and the standard errors could not be estimated under the bivariate probit model. Indeed, among the 26 traders who mainly sold to the modern channel and applied any damage control practices, only one trader adopted both chemicals and non-chemicals.

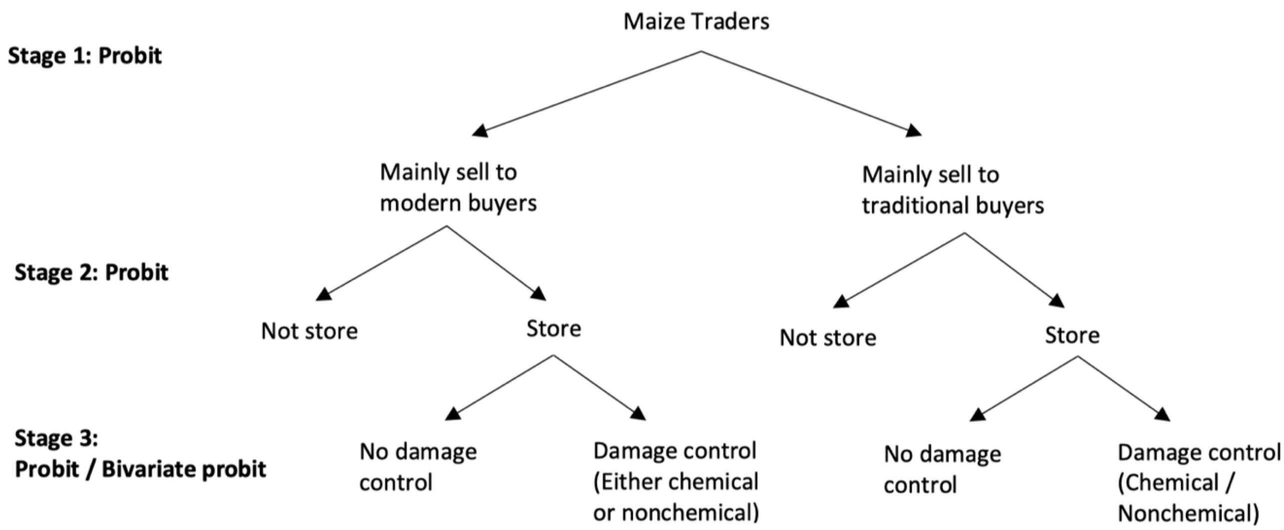

Figure 1. A triple-hurdle approach

We represent the full triple-hurdle specification as:

$$m_i = \beta_0 + \boldsymbol{\beta}_1 * \boldsymbol{v}_i + \beta_2 * p_i + \boldsymbol{\beta}_3 * \boldsymbol{k}_i + \boldsymbol{\beta}_4 * \boldsymbol{state}_i + \varepsilon_i \tag{5}$$

$$z_i^j = \gamma_0^j + \boldsymbol{\gamma}_1^j * \boldsymbol{v}_i + \gamma_2^j * p_i + \boldsymbol{\gamma}_3^j * \boldsymbol{k}_i + \boldsymbol{\gamma}_4^j * \boldsymbol{state}_i + \epsilon_i \tag{6}$$

$$\boldsymbol{x}_i^j | z_i = \theta_0^j + \boldsymbol{\theta}_1^j * \boldsymbol{v}_i + \theta_2^j * p_i + \boldsymbol{\theta}_3^j * \boldsymbol{k}_i + \boldsymbol{\theta}_4^j * \boldsymbol{state}_i + \xi_i \tag{7}$$

where m is the binary main market channel variable, whether trader i primarily sells to the modern ($m = 1$) or traditional ($m = 0$) channel, z^j is binary storage conditional on selling to market channel j, and $\boldsymbol{x}^j$ is a vector of binary damage control adoptions conditional on selling to market channel j and storage. We include explanatory variables $\boldsymbol{v}$, price p, and risks $\boldsymbol{k}$ in each regression as previously explained. In the first stage, (5), however, we do not include past experience of shocks in $\boldsymbol{k}$ since the reference period of the dependent variable, market channel choice, is prior to the reference period of shocks. Instead, we include yearly coefficients of variation of rainfall and temperature to account for long-term inter-year variability. In (6) and (7), $\boldsymbol{k}$ consists of past experience of shocks as well as monthly coefficients of variation during the period before the storage decisions are made. We additionally include a vector $\boldsymbol{state}$, which consists of four binary variables indicating each state, with Kaduna excluded as the base, in order to control for state specific effects. β_0, γ_0^j, and θ_0^j are constants, and ε_i, ϵ_i, and ξ_i are the error terms.

While parameters in all three stages can be estimated simultaneously by maximum likelihood estimation (MLE), the separability of the likelihood function allows to estimate: (i) $\boldsymbol{\beta}$ by a probit regression of m on the covariates; (ii) $\boldsymbol{\gamma}^j$ by a probit regression of z^j on the covariates only using observations who sell to j; and (iii) $\boldsymbol{\theta}^j$ by a (bivariate) probit regression of $\boldsymbol{x}^j$ on the covariates only using observations who sell to j and $z = 1$. In each state, we investigate the extent to which the risks affect traders' decisions regarding their primary market channel, storage (by market channel choice), and damage control strategies (by market channel choice and conditional on storage).

5. Results and Discussion

Table 2 presents the estimated marginal effects of the first and second stages. Results from the first hurdle indicate that variability in rainfall and temperature over the years in the long-term does not influence traders' main market channel choice. However, male traders and large-scale traders are more inclined to sell to modern buyers, while traders with longer trading experience and membership in trader associations are less likely to do so.

Columns (2) and (3) show how the storage decisions of traders selling to the modern and traditional channels are affected by different risks. The results reveal that higher rainfall variability does not affect the storage decisions of traders who sell mainly to the modern channel, but it adversely affects the storage decisions of those primarily selling to the traditional channel. Additionally, traders mainly selling to the modern channel tend to store maize in face of higher temperature variability, while traders mainly selling to the traditional channel tend not to store maize under similar conditions. This could be possibly because traders selling to the modern channel are more likely to be under contract with their buyers, hence striving to secure their maize by storing it to fulfill their contract, even when faced with adverse conditions. However, traders whose main buyers are in the traditional channel may choose not to store maize under high weather variability since storage under such conditions can result in maize damage. Therefore, they would opt to sell their maize immediately to buyers in demand.

For traders selling to the modern channel, our results indicate that the experience of conflict-induced shocks has a negative impact on their storage decisions. One possible explanation for this finding is that conflicts caused disruption in sourcing sufficient maize so that the traders might have been unable to spare maize for storage after delivering the designated amount to their modern buyers.

Table 3 presents the estimated marginal effects of risks on traders' implementation of damage control practices, given that they store maize. Column (4) shows that, provided that they sell to the modern channel and store maize, traders in areas with higher temperature variability are less likely to adopt any damage control practices. Similarly, conditional on selling to the traditional channel and storing maize (column (6)), traders in areas with high temperature variability are less likely to apply non-chemicals on stored maize. One plausible explanation for this could be that traders operating in areas prone to high temperature variability are already equipped with facilities that can protect stored maize from damage caused by temperature variation, or they may dry the maize before storing it, making it unnecessary to apply additional chemicals or non-chemicals.

Traders who had experienced spoilage shocks in the past are more likely to be more cautious and, thus, more likely to apply treatments to prevent damage to stored maize compared to those who had not experienced such shocks, regardless of their main market channel type. For traders who sell to the traditional channel and store maize, experience with conflict-induced shocks is likely to increase the chance of applying both chemicals and non-chemicals. On the other hand, experience with climate-induced shocks is likely to increase the chance of applying chemicals, which poses a safety challenge for maize, as chemical residues can be harmful when consumed, without affecting the likelihood of applying non-chemicals.

Our findings also indicate that receiving training in storage techniques is likely to decrease the chance of traders selling to the traditional channel to apply chemicals and non-chemicals. This suggests that traders who have received training may have better understanding and skills in protecting stored maize without relying on chemical and non-chemical treatments. In addition, we find that traders who engage in jobs besides maize trading are more likely to use chemicals and non-chemicals, as having multiple sources of income may have enabled them to invest in adopting these practices.

Table 2. Effects of risks on main market channel choice and storage

	First hurdle	Second hurdle	
VARIABLES	(1) Selling to modern market channel (Margins)	(2) Storage | modern market channel (Margins)	(3) Storage | traditional market channel (Margins)
Male (0/1)	0.153**	0.157**	0.102
	(0.0718)	(0.0679)	(0.0901)
Education (0/1)	0.0188	0.315***	-0.0339
	(0.0483)	(0.0828)	(0.0458)
Years of trading	-0.00545*	-0.00945***	-0.000612
	(0.00289)	(0.00307)	(0.00260)
Storage training (0/1)	0.0246	0.129	1.119***
	(0.102)	(0.0972)	(0.230)
Scale (0/1)	0.207***	0.147	0.00823
	(0.0406)	(0.0913)	(0.0467)
Distance to highway (km)	0.00143	0.00855**	-0.00597***
	(0.00230)	(0.00350)	(0.00211)
Trade Association (0/1)	-0.0981**	0.0894	0.0371
	(0.0477)	(0.0632)	(0.0467)
Other job (0/1)	-0.0156	-0.353***	-0.00673
	(0.0477)	(0.101)	(0.0520)
Price (Naira/ton)	2.92e-08	2.27e-06***	8.46e-08
	(1.22e-07)	(6.62e-07)	(1.77e-07)
CV of rainfall	-1.377	1.180	-0.343*
	(0.932)	(0.785)	(0.197)
CV of temperature	-26.90	17.75***	-17.39***
	(28.12)	(4.183)	(5.591)
Past climate shock (0/1)	-	-0.119	0.106
		(0.0820)	(0.0663)
Past spoilage shock (0/1)	-	0.0152	0.160
		(0.122)	(0.147)
Past conflict shock (0/1)	-	-0.138**	0.0777
		(0.0589)	(0.0519)
Kano State (0/1)	-0.336***	-0.192	0.181*
	(0.0938)	(0.435)	(0.104)
Katsina State (0/1)	-0.138*	0.315**	0.170
	(0.0775)	(0.129)	(0.109)
Oyo State (0/1)	0.774**	1.637***	-0.758*
	(0.362)	(0.471)	(0.448)
Plateau State (0/1)	0.269***	-0.356***	-1.126***
	(0.0601)	(0.0698)	(0.105)
Observations	839	197	642

Standard errors in parentheses

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

Table 3. Effects of risks on damage controlling of stored maize

	Third hurdle		
VARIABLES	(4) Use of any damage control practices | modern market channel and storage (Margins)	(5) Use of chemicals | traditional market channel and storage (Margins)	(6) Use of non-chemicals | traditional market channel and storage (Margins)
Male (0/1)	-0.0147	-0.0750	-0.119**
	(0.0704)	(0.0654)	(0.0485)
Education (0/1)	0.133	-0.0120	0.0395*
	(0.0912)	(0.0353)	(0.0233)
Years of trading	-0.000594	0.00160	0.00204*
	(0.00342)	(0.00165)	(0.00120)
Storage training (0/1)	-	-0.857***	-0.533***
	(omitted)	(0.128)	(0.115)
Scale (0/1)	0.0336	0.0136	0.0551
	(0.0812)	(0.0364)	(0.0345)
Distance to highway (km)	-0.0357***	0.000636	0.00273**
	(0.0101)	(0.00172)	(0.00138)
Trade Association (0/1)	0.198**	-0.0525	-0.0334
	(0.0772)	(0.0376)	(0.0212)
Other job (0/1)	-	0.0760*	0.0615**
	(omitted)	(0.0426)	(0.0301)
Price (Naira/ton)	-7.26e-07	6.57e-08	9.16e-08
	(5.84e-07)	(3.06e-07)	(7.15e-08)
CV of rainfall	-0.954	-0.0486	-0.122
	(0.615)	(0.140)	(0.0967)
CV of temperature	-44.73***	0.940	-5.684**
	(17.34)	(4.684)	(2.815)
Past climate shock (0/1)	0.0611	0.103**	0.00217
	(0.0630)	(0.0399)	(0.0240)
Past spoilage shock (0/1)	0.621***	0.296***	0.0947***
	(0.211)	(0.0768)	(0.0365)
Past conflict shock (0/1)	0.0723	0.0782*	0.0545*
	(0.0609)	(0.0420)	(0.0290)
Kano State (0/1)	-0.574***	0.269***	-0.0837
	(0.178)	(0.0710)	(0.0593)
Katsina State (0/1)	-0.604***	0.0325	-0.117*
	(0.176)	(0.102)	(0.0664)
Oyo State (0/1)	-3.186**	0.168	-0.921***
	(1.316)	(0.336)	(0.284)
Plateau State (0/1)	-0.111*	-	-
	(0.0648)	(omitted)	(omitted)
Observations	96	448	448

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Conclusion

This study examined the impact of various risks on the decisions of Nigerian maize wholesale traders regarding their primary market channel, adoption of storage, and application of chemicals and/or non-chemicals to stored maize. Maize traders play a critical role in the Nigerian economy, as the production and consumption of maize serve as a cornerstone of the country's food system. In particular, their storage behaviors, including the use of chemicals and/or non-chemicals, impact the quantity and quality of maize that reaches consumers, and are therefore linked to issues of food security and safety.

The decision of traders to store maize and apply damage control practices is likely to be influenced by their choice of market channel. Traders who sell mainly to modern buyers are more likely to prioritize meeting the requirements and maintaining the quality of their maize as specified by their buyers. Consequently, they may have different incentives when it comes to making decisions about storage and damage control compared to traders who sell primarily to traditional buyers. We adopted a triple-hurdle model to account for this initial stage of market channel choice.

We find that the variation in temperature in the area where traders operate their business affects the storage decisions of traders selling to both modern and traditional buyers, but in opposite directions. For traders selling to modern buyers, higher temperature variability increases the likelihood of storing maize, whereas for those selling to traditional buyers, it reduces the likelihood of storage. This may be because traders selling to modern buyers have a stronger incentive to secure maize and be prepared for potential sourcing disruptions to continue meeting buyers' demand.

Moreover, our results show that past experience of climate-induced shocks has no statistically significant effect on damage control adoption among traders selling to modern buyers. However, it has a positive effect on the application of chemicals among traders selling to traditional buyers. Given that the majority of traders mainly sell to traditional buyers, an increase in chemical applications in association with climate-induced shocks raises concerns about the safety of maize.

This study sheds light on maize traders' adaptation to multiple risks. Given that many agrifood value chains in developing countries are increasingly exposed to climate-, conflict-, and/or spoilage-related risks, this study provides important insights into understanding the impacts of the risks and building more resilient systems. Furthermore, understanding how midstream actors respond and adapt to risks depending on certain characteristics, such as their primary market channel as examined in this study, is crucial for addressing these risks more efficiently. Thus, we recommend that policies aimed at mitigating the impact of risks and building a more resilient maize value chain in Nigeria should take into account the differential effects of risks on traders selling to different market channels.

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