ESSAYS ON TRANSFORMING AGRIFOOD VALUE CHAINS IN SUB-SAHARAN AFRICA: IMPACTS, DYNAMICS, AND POLICY PERSPECTIVES

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ABSTRACT

This dissertation explores the intricate dynamics of agrifood value chains in Sub-Saharan Africa (SSA), examining the interplay between policy interventions, market responses, and the challenges encountered by value chain participants. The first essay examines the unintended impacts of agricultural input subsidy programs (ISPs) on smallholder farm households' dietary diversity. Despite ISPs' resurgence in SSA as popular policy tools for intensifying agricultural production and ultimately improving food security, questions persist regarding their effects on households' access to diverse food. Using nationally representative household panel data from Zambia, I investigate the potential underlying mechanisms through which Zambia's Farmer Input Support Programme (FISP) may influence smallholders' household dietary diversity scores (HDDS) employing a fixed effects instrumental variables approach. Contrary to prior findings, the analysis uncovers a negative association between FISP fertilizer subsidies and HDDS. The program's pronounced emphasis on maize fertilizer appears to have incentivized beneficiary households to allocate more resources to maize cultivation, to the detriment of both crop production diversity and crop income, thereby negatively affecting HDDS.

In the second essay, I investigate the impacts of various risks stemming from climate change, violent conflicts, and spoilage on the often-overlooked middle segment within agrifood value chains. Using data from a survey of maize wholesale traders in Nigeria's major maize-producing and consuming states, I explore traders' maize storage behaviors in response to prevailing weather risks and past experience of weather, conflict, and spoilage shocks, based on their primary market channel. Given potential disparities in contract design and quality standards between the modern market channel (e.g., industrial food and feed mills) and traditional market channel (e.g., retailers, other wholesalers, and consumers), traders may adapt their storage

behaviors accordingly. I use a triple-hurdle model to incorporate the initial stage of traders' selection of their primary market channel. Subsequently, I examine how these diverse risks are associated with traders' decision to store maize and then specific damage control practices (i.e., applying chemicals or using non-chemical methods) among those opting for storage. I find that traders selling to the traditional channel opt to promptly sell maize amid high rainfall and temperature variability and use chemicals on stored maize when previously confronted with adverse shocks. In contrast, traders selling to the modern channel tend to store maize even under unfavorable weather conditions to compensate for potential losses from risks and to consistently fulfill contractual obligations. Concerned with preserving maize quality with minimal chemical residues, these traders do not appear to apply chemicals unless they were previously exposed to spoilage shocks.

In the third essay, I investigate the preferences of Nigerian maize wholesale traders regarding policies to address conflict and weather shocks. With growing concerns about the multifaceted challenges faced by agrifood value chains in SSA, understanding the perspectives of value chain participants becomes vital for designing effective policies to address the challenges. I use the best-worst scaling (BWS) method to evaluate maize traders' preferences across various policy options. This includes nine alternative policy options for addressing violent conflicts and eight aimed at mitigating extreme weather events; these are also categorized as hard and soft infrastructure policy measures. The BWS experiment reveals that traders make trade-offs between soft and hard infrastructure policy options depending on the type of shocks encountered. Additionally, traders' demographic and business characteristics significantly influence their policy preferences, highlighting the need for tailored policy responses aligned with the specific nature of shocks and trader characteristics.

Dedicated to my dear and loving mother.

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CHAPTER 1:

UNINTENDED CONSEQUENCES OF INPUT SUBSIDIES ON HOUSEHOLD INCOMES, PRODUCTION DIVERSITY, AND DIETARY DIVERSITY

1.1 Introduction

Agricultural intensification has accelerated over the past few decades, enabling more people to consume sufficient quantities and calories, particularly from cereal crops (Ickowitz et al., 2019). However, the improvement in access to quality, diverse, and nutritious diets has not kept pace (Haddad et al., 2015; Pinstrup-Andersen, 2013). Notably, most current agricultural and food security policies in developing countries tend to concentrate narrowly on the availability of staple crops and energy intake (Ickowitz et al., 2019).

Input subsidy programs (ISPs) are popular, yet costly, policy tools used by governments in Sub-Saharan Africa (SSA) with the goal of intensifying agricultural production (Jayne and Rashid, 2013) and ultimately improving incomes and food security. Considerable research has analyzed the impacts of ISPs on various outcomes, including fertilizer use (Gignoux et al., 2022; Jayne et al., 2018; Jayne et al., 2013; Xu et al., 2009a); food price levels (Arndt, Paw, and Thurlow, 2016; Ricker-Gilbert et al., 2013; Takeshima and Liverpool-Tasie, 2015); crop yields (Gignoux et al., 2022; Karamba and Winters, 2015; Mason, Jayne, and Mofya-Mukuka, 2013; Wossen et al., 2017); cropping patterns, cropland allocation, and/or crop diversification (Ahmad et al., 2022; Chibwana, Fisher, and Shively, 2012; Holden and Lunduka, 2013; Kankwamba, Mapila, and Pauw, 2012; Karamba, 2013; Kuntashula and Mwelwa-Zgambo, 2022; Mason et al., 2017; Mofya-Mukuka and Hichaambwa, 2018; Morgan et al., 2019; Saenz and Thompson, 2017; Smale and Thériault, 2022; Snapp and Fisher, 2015; Thériault and Smale, 2021); commercialization of agricultural production (Fujimoto and Suzuki, 2021; Sibande, Bailey, and Davidova, 2017); as well as household incomes and/or poverty (Kijima, 2022; Mason and Smale, 2013; Mason and Tembo, 2015; Mason et al., 2017; Smale and Thériault, 2022; Wossen et al., 2017), among other outcomes.[1] Studies have also assessed the effects of ISPs on food security measures like caloric acquisition (Gilligan, Hoddinott, and Taffesse, 2009) and food expenditure (Karamba, 2013; Tossou and Baylis, 2018; Wossen et al., 2017).

However, limited attention has been given to the impacts of ISPs on nutrition, dietary quality, and/or diversity outcomes, which are also crucial components of food security. Some researchers have assessed how ISPs influence child nutrition and/or health (Chakrabarti et al., 2024; Chirwa et al., 2013; Harou, 2018; Holden and Lunduka, 2013; Karamba, 2013). Others have examined the relationship between ISPs and dietary diversity, but the findings are mixed and focused on a few countries. Subsidized fertilizer increased the likelihood of women consuming a more diverse diet within Malian farming households (Smale, Thériault, and Mason, 2020). Notably, Assima, Zanello, and Smale (2022) observed a similar positive association between the Malian ISP and women's dietary diversity in one agroecological region, while identifying a negative relationship in another. In Malawi, households benefiting from the subsidy program showed more frequent consumption of various food groups (Harou, 2018) and improved dietary diversity (Snapp and Fisher, 2015; Matita et al., 2022; Novignon, Chirwa, and Frempong, 2020). On the other hand, in a unique setting where beneficiaries were randomly selected, Gine et al. (2015) found that Tanzania's ISP did not have a statistically significant influence on household dietary diversity.

In the context of Zambia, two studies have assessed the influence of Zambia's ISP, specifically the Farmer Input Support Programme (FISP), on the dietary diversity of smallholder households. One study centers on how shifts in FISP input choices impact beneficiary

[1] For comprehensive reviews of the literature on ISPs, refer to Holden (2019) and Jayne et al. (2018).

households' maize production and dietary diversity (Tossou and Baylis, 2018). Employing a household fixed effects model, they found that a recent change in FISP to encompass a broader range of agricultural inputs beyond fertilizer and seed led to an enhanced dietary diversity among beneficiary households. It is important to note that this conclusion relies on the assumption that any omitted household or farm characteristics are time-invariant, which may not always hold. Another piece of evidence reports that FISP has a positive association with various measures of production diversity as well as household dietary diversity (Kuntashula and Mwelwa-Zgambo, 2022). This conclusion is drawn from cross-sectional data covering the 2013/14 agricultural year, with households matched based on observational characteristics.

Despite evidence suggesting that ISPs can have significant implications for nutritional outcomes and households' access to diverse foods, a critical gap remains in understanding the underlying mechanisms through which input subsidies translate into such outcomes. Recently, Chakrabarti et al. (2024) explored the connections between input subsidies and child nutrition in the context of Malawi, examining the ISP's influence through crop production and diversity, income, and female empowerment. Similarly, Smale, Thériault, and Mason (2020) and Assima, Zanello, and Smale (2022) investigated the links between input subsidies and women's dietary diversity in Mali, focusing on production and income channels. Regarding households' access to diverse foods, Snapp and Fisher (2015) found that fertilizer subsidies are positively associated with crop diversity and the adoption of modern maize varieties in Malawi, which could potentially enhance household dietary diversity.

We build on this literature by investigating how the Zambian FISP is associated with household dietary diversity, assessed by the household dietary diversity score (HDDS). This investigation involves the analysis of two main potential impact pathways: the production pathway and the income pathway. Specifically, we estimate the effects of FISP on (i) the diversity of crops cultivated on farms, measured by the Simpson index of diversification (SID) for field crops, and (ii) household income, with a focus on farm income calculated as the net value of agricultural production.

We use data from two waves of nationally representative household panel surveys: the 2015 and 2019 Rural Agricultural Livelihoods Survey (RALS). Additionally, we incorporate supplementary data such as rainfall and local election records. To account for potential self-selection bias among beneficiary farmers into FISP, we employ a fixed effects instrumental variables (FE-IV) approach. Unlike prior findings that indicated a positive association between FISP and household dietary diversity, our study interestingly reveals a negative impact on it when accounting for both time-invariant and time-varying unobservables. This negative link appears to be driven by the more maize-centric production by FISP beneficiaries, resulting in both a decrease in crop diversity on farms and reduced household income for purchasing a variety of foods.

This study contributes to the literature on ISPs in SSA by examining their impacts on household dietary diversity, an important measure of households' access to food and diversified diets. Zambia has implemented one of the most substantial ISPs in SSA, allocating approximately 50% of government agricultural sector expenditure to FISP in 2017, yet there persists a need for more comprehensive and rigorous evidence regarding its effects on household dietary diversity and associated mechanisms. Specifically, our study explores two underlying pathways connecting ISPs to smallholder household dietary diversity and delves further into the factors that drive the effect of FISP on the intermediate outcomes of production diversity and household income. While assessing the impact of ISPs on food security outcomes is crucial, understanding the mechanisms actually driving these outcomes is key for informed policy decisions.

In addition, unlike matching techniques employed in Snapp and Fisher (2015), which solely rely on observables, we adopt the FE-IV approach to tackle the endogeneity concern stemming from beneficiaries' self-selection into the program. Once we account for both time-invariant and time-varying household-specific omitted attributes, our findings diverge from those of most other ISP studies, including the two specific Zambian studies. Furthermore, this research expands upon the existing literature that evaluates the relationship between ISPs and farm production diversification (for instance, Nkonde et al., 2021), as well as the limited body of work investigating the link between ISPs and household income in Zambia (Mason and Smale, 2013; Mason and Tembo, 2015).

1.2 Background

Zambia's Farmer Input Support Programme

Maize serves as the main target crop for the Government of the Republic of Zambia's (GRZ) central mechanisms in the agricultural and food security policy domain. These mechanisms involve administering a strategic grain reserve and buying/selling maize via the Food Reserve Agency (FRA), and implementing agricultural input subsidies via FISP.[2] The objective of FISP is to enhance the provision and distribution of agricultural inputs to small-scale farmers to improve household food security and income levels (MoA, GRZ, 2018).[3]

[2] The Food Reserve Agency (FRA) operates as a parastatal responsible for the procurement and distribution of maize, as well as the management of the national strategic grain reserve. In surplus production regions, the FRA acquires maize from smallholder farmers at price that generally surpasses the market price, subsequently engaging in sales or exports (Mason, Jayne, and Van De Walle, 2017). Additionally, the FRA administers the national grain reserve that functions as a buffer stock during periods of low harvest or shortages. This reserve aims to stabilize maize prices and maintain the maize prices at an affordable level for consumers (Chapoto et al., 2016).
[3] Eligible farmers, meeting specific criteria such as membership in a cooperative or farmer group, payment of the farmer contribution, and capacity for cultivating at least 0.5 hectares of maize (but less than 5 hectares), apply for FISP. Beneficiaries are selected by local leaders, extension officers, and the board of farmer cooperatives.

The GRZ has implemented various forms of ISPs since the 1990s. In the 2009/10 agricultural year, FISP was introduced, and later transitioned to the e-Voucher FISP in 2015/16, featuring an electronic voucher system. The conventional FISP, heavily centered on maize, provided a standard input package distributed through farmer groups, including basal dressing fertilizer (100kg), top dressing fertilizer (100kg), and hybrid maize seed (10 kg). Subsidy levels ranged from 50-80% for fertilizer and 50-100% for maize seed.

To encourage private sector engagement in input procurement and distribution, the e-Voucher system was piloted in the 2015/16 agricultural year and later expanded nationwide in 2017/18. The system issues electronic vouchers redeemable at approved private suppliers and agro-dealers, allowing beneficiaries to choose inputs based on their specific needs, promoting diversification. This includes seeds and fertilizers for various crops, farming equipment, and supplies related to livestock and fisheries. The e-Voucher was priced at Zambian Kwacha (ZMW) 2,100 in the 2017/18 agricultural year, with farmers contributing ZMW 400, while the GRZ provided significant support of ZMW 1,700, representing approximately 8% of the average stallholder household income (Chapoto and Subakanya, 2019).

The 2015 RALS, our panel's first wave, corresponds to the 2013/14 agricultural year under the conventional FISP, while the 2019 RALS, our second wave, covers 2017/18 when the e-Voucher system was first implemented nationwide. However, challenges like the lack of private sector distributors and poor internet connectivity for processing the e-Voucher resulted in a return to the conventional system in some districts from the 2018/19 agricultural year. Despite efforts to promote diversification, maize fertilizer still constituted over 90% of total distributed inputs through FISP in 2018/19 (MoA, GRZ, 2018). This figure, although slightly reduced from the 95% observed in 2013/14 (MAL, GRZ, 2014), still highlights the predominant focus of FISP on maize fertilizer even with the introduction of the e-Voucher system.

Interplay of Input Subsidies and Household Dietary Diversity

Figure 1.1 presents a conceptual framework illustrating two primary pathways through which ISPs might affect household food consumption and dietary diversity, mediated by various factors: the production pathway and the income pathway. Subsidies for inputs used in cultivating staple crops may lead to increased staple crop production, encouraging smallholders with relatively abundant cropland to allocate some of their cropland to other crops, hence fostering farm production diversity (Snapp and Fisher, 2015). In environments where access to consumer food markets is restricted, diversifying agricultural production could directly raise dietary diversity as most of what household members eat comes from what the household produces (e.g., Bellon et al., 2020). A recent review highlights that 19 out of 21 studies discovered a positive association (though not necessarily a causal relationship) between agricultural production diversity and dietary diversity (Jones, 2017). Sibhatu and Qaim (2018) also reported, based on a review of the literature, that the average marginal effect of production diversity on smallholder farm households' dietary diversity tends to be positive, albeit small.

However, for smallholders with severe food insecurity or constrained cropland, subsidizing staple crop production may simply result in more staple crop production at the expense of other crops, leading to crop simplification (Chibwana, Fisher, and Shively, 2012; Morgan et al., 2019). Enhanced agricultural production via input subsidies, whether focused on more diverse crops or staple crops, may raise farm income by increasing the value of agricultural production while reducing fertilizer costs. Farm income, along with off-farm income and other sources, constitute household income that the household can use to purchase diverse food from the market (Snapp and Fisher, 2015). Nonetheless, higher income does not necessarily translate to improved dietary diversity. Poor transportation infrastructure or limited variety in the local production system can hinder the availability of diverse food options in local markets (Ickowitz et al., 2019). Even if the local markets offer diverse foods, households might choose not to purchase and consume them.

A major intervening factor in the income pathway is the share of off-farm income. Access to subsidized inputs provides households with more disposable income, particularly for those with restricted off-farm income prospects, allowing strategic investments in their farms. This investment may yield increased output or production of commercial products and potentially foster market engagement. Conversely, households with abundant off-farm income streams (such as those residing near urban centers) might redirect resources away from farming to pursue off-farm income avenues, which can offer higher and more consistent returns than farm activities (Kilic et al., 2009). Therefore, the interactions between input subsidies and household production diversity, income, and dietary diversity are inherently context-specific and warrant empirical investigation.

1.3 Data and Variables

Data

The Rural Agricultural Livelihood Survey (RALS) is a nationally representative household panel survey conducted via a collaboration between the Indaba Agricultural Policy Research Institute and the Zambia Central Statistical Office, Ministry of Agriculture, and Ministry of Fisheries and Livestock. Encompassing the 2013/2014 and 2017/2018 agricultural years, the 2015 and 2019 RALS surveys provide a comprehensive overview of Zambia's rural livelihoods and the small- and medium-scale agricultural sector (i.e., households cultivating less than 20 hectares). In the RALS 2015, 7,934 households from 476 standard enumeration areas (SEAs) across Zambia's 10 provinces were interviewed.[4] In the RALS 2019, 7,241 of the RALS 2015 households were re-interviewed, with the attrition stemming primarily from households relocating outside the study area. To address potential bias from attrition, we conducted a regression-based test (Wooldridge, 2010) and found no significant indications of attrition bias (details in Appendix B, Table 1.6).

Figure 1.2 illustrates the timeline of various seasons and FISP distributions for RALS 2015; a similar timeline applies for RALS 2019. The 2015 survey took place in June-July of 2015 and gathered data on farming and marketing activities for the 2013/14 agricultural year (where the latter is defined as October 1st, 2013-September 30th, 2014). The 2013/14 growing season extended from October 1st, 2013 to April 30th, 2014, and the 2014/15 marketing year followed from May 1st, 2014 through April 30th, 2015, with the peak marketing season occurring between May 1st and September 30th, 2014. During the 2015 survey, information regarding the 2013/14 FISP was collected; we refer to this as the "previous" FISP. Subsidized inputs were distributed in the early part of the 2013/14 agricultural year, potentially influencing production diversification decisions throughout the 2013/14 agricultural year (captured as the production pathway) and household income during the 2014/15 marketing year (captured as the income pathway). Ultimately, this may have impacted household dietary diversity, which was assessed during the interview period (June-July 2015). The survey also gathered data on the "recent" FISP (i.e., the 2014/15 FISP). However, we focus on the *previous* FISP, as the comprehensive impact of the *recent* FISP cannot be captured due to data limitations and reference period issues. See Appendix B, Figure 1.3 for more details.

In the remainder of section 1.3, we outline the outcome variables (crop production diversity, household income, and household dietary diversity scores), measures of FISP, and

[4] SEAs are the smallest geographic units in the sampling process. See Chapoto and Zulu-Mbata (2016) for details on the two-stage sampling process used for the RALS.

control variables that are ultimately used in the FE-IV regressions. In section 1.4, we provide a more detailed description of the FE-IV regressions, as well as the instrumental variables and identifying assumptions.

Crop Production Diversity and Household Income

While livestock and fisheries are undoubtedly crucial components of agricultural livelihoods, our analysis specifically focuses on crop production. This focus is underscored by the importance of land and crop-based agricultural systems in Zambia, along with the FISP's emphasis on field crop production (Chapoto and Subakanya, 2019). To measure field crop production diversity, we employ the Simpson index of diversification (SID), which measures proportional abundance by assessing both richness (i.e., the number of distinct plants) and the relative abundance (i.e., the evenness of their distribution) of plant populations (Hill, 1973; Magurran, 1991). Originating in ecological studies, the SID has been adapted and widely used to assess on-farm crop diversity in household-level analyses (Bellon et al., 2020; Joshi et al., 2004; Meng et al., 1998; Smale, 2006; Verger et al., 2021).

The field crop SID for the 2013/14 (2017/18) growing season is computed as follows:

$$SID = 1 - \sum_{j=1}^{J} P_j^2$$

where P_j represents the proportionate area of the j^{th} crop within the household's total cropped area. The RALS data cover 22 distinct crops, including cereals, legumes, root and tubers, oilseed crops, and sugarcane. The SID values range from 0 to 1, with 0 indicating complete specialization in a single crop, and higher scores reflect a greater diversity of distinct crops that are more evenly distributed across fields. Additionally, we supplement our analysis with the Herfindahl index ($\sum_{j=1}^{J} P_j^2$), which is equal to one minus the SID and is derived from the economics literature to measure market concentration (Rhoades, 1993). This index has been applied to assess land allocation concentration across different crops (Meng et al., 1998; Pope and Prescott, 1980; Thériault and Smale; 2021), where a higher value indicates a greater concentration of field area in certain crops and less evenness.

Household income is measured by the net income (in ZMW) sourced from various observed channels, including both net farm income and net off-farm income in real 2014/15 ZMW. (That is, 2018/19 values were deflated to real 2014/15 terms using the consumer price index.) Net farm income is derived by adding up the total gross value of field crop, vegetable, and fruit production, the income generated from the sale of live and slaughtered animals as well as the value of animals slaughtered for home consumption, the value of eggs, milk, broilers, and fish production, then subtracting the total cost of fertilizers (Chapoto and Zulu-Mbata, 2016).[5] The total cost of fertilizers was calculated by taking into account the varying prices of purchased commercial fertilizers, subsidized fertilizers, and fertilizers that were granted. Net off-farm income is calculated by summing up earnings from salaried employment and informal wage labor (whether in the form of cash or in-kind payments), pensions, remittances (both cash and goods), and income generated from formal and informal business activities, then deducting the total expenses incurred in conducting these business activities.

Household Dietary Diversity

Dietary diversity, the variety of food groups consumed over a specific period, is a crucial component of a healthy diet. At the individual level, it serves as an indicator of dietary quality and nutrient adequacy (Verger et al., 2019), with substantial evidence linking it to improved health and food security outcomes (see, for example, Arimond et al., 2010; Ruel, Harris, and Cunningham, 2013). At the household level, dietary diversity reflects a household's economic

[5] Due to data limitations, the costs of other inputs used could not be incorporated.

ability to access a diverse range of foods to meet the nutritional requirements of its members (Swindale and Bilinsky, 2006; Verger et al., 2019). Evidence suggests that household dietary diversity serves as a proxy for household food access and is positively associated with per capita caloric availability from both staples and non-staples within households (see, for example, Hoddinott and Yohannes, 2002; Kennedy et al., 2010; Leroy et al., 2015).

Given the objective of this study to investigate the impact of ISPs on dietary diversity from the perspective of household-level crop production diversity and income, we use the household dietary diversity score (HDDS) to assess smallholder households' access to a variety of foods, a crucial aspect of food security. The HDDS is the number of food groups (selected from a list of 12 distinct groups) consumed by the household within the last 24-hours (Swindale and Bilinsky, 2006). The RALS 2015 and 2019 surveys gathered self-reported information on the consumption of 16 distinct food groups. Respondents reported which groups were prepared and consumed in their households during the 24 hours preceding the interview. To create a standard HDDS, we combined several of these groups into a list of 12: cereals; roots and tubers; milk and milk products; vegetables; fruits; meat, poultry, and offal; eggs; fish; legumes, nuts, and seeds; oils and fats; sweets such as sugar and honey; and miscellaneous (spices, condiments, and beverages). HDDS is between 0 and 12, with a higher score indicating a more diversified dietary intake and greater food access at household level.

FISP Participation

Households' participation in FISP can be measured in various ways. One method is binary categorization, assigning a value of 1 if the household received any subsidized inputs and 0 otherwise. This approach, however, does not capture the heterogeneity in input quantity and types received by different households. FISP inputs are distributed at an individual level, potentially leading some households to have multiple beneficiaries. Additionally, even though beneficiaries were expected to receive a standardized package under the conventional FISP, the actual amount and proportion of distributed inputs varied among beneficiaries. Hence, an alternative way to gauge a household's participation in FISP is to construct a scalar measure that aggregates the value or quantity of inputs received.

While these two measures would be ideal, data constraints in RALS lead us to focus on fertilizers, the major FISP input.[6] We measure FISP fertilizer participation in two ways: (i) binary receipt (=1 if the household received any FISP fertilizer, and =0 otherwise); and (ii) total kilograms (kg) of FISP fertilizer received.[7] Scrutinizing these two measures can serve as a means to bolster the robustness of our findings.

Control Variables

Drawing on a theoretical framework rooted in an agricultural household model (see Appendix C), we include control variables incorporating household, farm, and market characteristics, detailed in Table 1.1 along with summary statistics. The number of full-time adult equivalents (FTAE) serves as a proxy of both household size and available labor resources. Metrics like household landholding size and the total value of productive assets (livestock and farm equipment) are included as measures of household wealth. We also control for the market prices of the main agricultural input (basal dressing fertilizer) and output (maize). The prices and value of productive assets are in real 2014/15 ZMW.

Years of e-Voucher FISP implementation are included as the duration varies across

[6] Additional details on the FISP participation captured in the RALS are provided in Appendix B, Table 1.7.
[7] In roughly 90% (92%) of the cultivated fields where basal (top) dressing fertilizer was applied, compound D (Urea) was the chosen type. While these fertilizers differ in terms of their nitrogen-phosphorus-potassium ratios, and despite our attempt to standardize them based on nitrogen nutrient kilograms, our instrumental variables (discussed in section 1.4) did not exhibit significant relevance to the standardized amount of FISP fertilizers. Hence, we proceed with the simple total amount in kilograms.

districts.[8] This could impact the inputs for which households' redeem e-Vouchers, potentially affecting their decisions regarding agricultural production, income activities, and diverse food consumption. Access to agricultural input and output markets is also pivotal in shaping smallholders' production and consumption decisions. We account for distances from a household's homestead to the nearest tarred road, agro-dealer, and local marketplace. Distances to the nearest FRA buying points during different seasons are included as measures of maize market access and the maize marketing policies of FRA. Additionally, rainfall plays a critical role in crop production and productivity in Zambia, given smallholders' reliance on rainfed agriculture (Mofya-Mukuka and Hichaambwa, 2018). Utilizing district-level daily rainfall data sourced from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), we calculated total rainfall during the growing season, November 2013 (or 2017) through March 2014 (or 2018) (Mason et al., 2017; Morgan et al., 2019).

Cell phone ownership represents access to information like farm produce prices, weather forecasts, and extension services. Plough ownership indicates whether a household owned an ox-drawn plough and/or a disc plough during planting time. Plough ownership rates were below 30%, suggesting low mechanization as a potential constraint to crop production (Sichoongwe et. al., 2014). Additionally, we integrate membership status in a farmer cooperative, group, or association, which is one of the eligibility criteria for FISP participation. Such membership is likely to be positively associated with access to information and extension services.

Different sets of control variables are included in different analyses, considering their reference period and relevance to the field crop SID, household income, and HDDS. In the

[8] In specific terms, for the 2017/18 agricultural year, the e-Voucher FISP had been implemented for 3 years for households living in the first pilot districts during the 2015/16 agricultural year, 2 years in districts incorporated in the second pilot year (2016/17), and 1 year in districts newly introduced to the e-Voucher system in its nationwide implementation in 2017/18.

HDDS regression, all relevant control variables are incorporated. For the field crop SID analysis, although the reference period for calculating the value of productive assets is after the reference period for the field crop SID, we proceed with the assumption that the value of productive assets remains relatively stable over time and incorporate it into our analysis. We could not include the off-farm income share and cell phone ownership in the SID regression due to the same reference period conflict. However, landholding size can serve as a proxy for household wealth or assets (Mofya-Mukuka and Hichaambwa, 2018) in the absence of an income measure (i.e., off-farm income share).

For the household income analysis, we omit the distance to the nearest agro-dealer and the price for basal fertilizer from the regression, as their impact is factored into the household income net of input costs. Plough ownership, not directly influencing household income, is also omitted, and its value is reflected in productive assets. (Estimation results are robust to the inclusion of these variables.) Conversely, cell phone ownership and farmer cooperative/group membership, not considered in the field crop SID analysis, are included in the income regression. Such membership has been found to enhance farmers' bargaining power and improve access to market information (Kahenge, Muendo, and Nhamo, 2019).

1.4 Identification Strategy and Instrumental Variables

We estimate regressions of the following form, where households are indexed by i:

$$DV_{it} = \beta_0 + \beta_1 FISP_{it} + \beta_2 Year_t + \boldsymbol{V}_{it}\boldsymbol{\beta_3} + a_i + \varepsilon_{it}$$

The dependent variable (DV) is either the field crop SID, household net income, or HDDS for the agricultural years 2013/14 and 2017/18, corresponding to survey waves $t = 2015$ and 2019, respectively. The term β_0 is the constant, and the indicator variable $Year_t$ (1 for 2019 and 0 for 2015) accounts for year-specific factors or shocks shared by all households within a particular year.[9] The vector $\boldsymbol{V}_{it}$ stands for the control variables, as indicated in Table 1.1. The term a_i captures household-specific, time-invariant factors, and ε_{it} represents the idiosyncratic error term. The main explanatory variable of interest, $FISP_{it}$, indicates households' FISP beneficiary status, either binary or the total amount of fertilizer received. These models are estimated via FE-IV using the IVs for FISP described below. (First-stage results and IV diagnostics are discussed in the results section.)

Measuring the impacts of FISP presents challenges due to its non-random distribution among beneficiaries, as in many other ISPs (Ricker-Gilbert, Jayne, and Shively, 2013). Indeed, Mason, Jayne, and Mofya-Mukuka (2013) found that FISP fertilizer allocation tends to favor wealthier households and those cultivating larger areas.[10] To tackle potential selection bias and endogeneity issues, we employ an FE-IV strategy. Adopting a fixed effects approach enables us to control for household-specific unobservable factors that remain constant over time and could affect decisions related to production, income, dietary diversity, and FISP participation. Nonetheless, we cannot rule out the possibility of time-varying unobserved factors that may predict the outcomes and correlate with FISP participation. For example, households with farmers who have acquired better agricultural knowledge over time may be more inclined to self-select into the FISP, as well as to engage in diversified crop production, generate higher income, and consume more diverse diet. Overlooking such unobserved, time-varying traits could lead to

[9] Although there have been changes to the structure of the FISP between the two panel years (i.e., transitioning from the conventional FISP in the 2013/14 agricultural year to the e-Voucher FISP in the 2017/18 agricultural year), the actual impact of the program change on the outcomes measured here may have been negligible. Given that the 2017/18 agricultural year marked the first nationwide implementation of the e-Voucher system, beneficiaries had a limited understanding of the new program and continued to redeem the vouchers for fertilizer as before (MoA, GRZ, 2018). Additionally, year fixed effects partially account for potential changes that the program's change might have induced.

[10] While eligibility criteria exist for FISP participation, they were not strictly enforced, impeding the application of regression discontinuity design. For example, one of the eligibility criteria limits FISP participation to households cultivating less than 5 hectares. Nevertheless, 50% of households cultivating more than 5 hectares received FISP inputs (Mason, Jayne, and Mofya-Mukuka, 2013).

an overestimation of FISP's impact on these outcomes. Consequently, by combining FE with IV, we address the potential bias from time-varying household-level omitted factors.

Following Mason and Ricker-Gilbert (2013), we constructed two locality-based electoral variables as candidate IVs, using Zambian parliamentary election results from the National Assembly and the Electoral Commission of Zambia.[11] The first variable is binary, taking the value of 1 if the member of parliament in the household's constituency is affiliated with the ruling party that won in the most recent presidential election, and 0 otherwise. The second variable is the absolute value, in percentage points, of the difference between the share of votes obtained by the ruling party and the leading opposition party in each constituency; this reflects the tightness of the race. We use 2011 Zambian general election data for the 2013/14 FISP, and 2016 general election data for the 2017/18 FISP.

These two election variables, along with their interaction, serve as instruments for the binary FISP fertilizer receipt model specifications and the total kg of FISP fertilizer received model specifications. Considering the political context of the subsidy program in Zambia (Mason, Jayne, and van de Walle, 2017), we hypothesize that the ruling party government (Patriotic Front in both the 2011 and 2016 elections) directs more subsidized fertilizer to constituencies where it won. Thus, households are more likely to receive FISP fertilizer, and they are also more likely to obtain a larger quantity of it, if the ruling party won in their constituencies, and more so the larger the margin of victory.

We assume that the results of the elections do not directly impact households' decisions

[11] We have explored several potential instruments commonly used in the ISP literature, such as the duration the household head has resided in the area as seen in studies like Chibwana, Fisher, and Shively (2012) and the count of district-level pre-allocated beneficiary packs as observed in works like Novignon, Chirwa, and Frempong (2020). However, in the context of our household fixed effects framework, we did not observe a sufficiently strong partial correlation between FISP fertilizer and either of these two variables.

regarding production diversity, income, and dietary diversity. Instead, such effects come only through their impact on households' participation in FISP. As election outcomes represent the decisions of numerous households and households are unlikely to relocate across constituencies solely to access more subsidized inputs, the direct influence of election results on the dependent variables is likely to be zero or negligible. While it is conceivable that local election results could influence the dependent variables through other food and agricultural policies, it is noteworthy that input subsidies through FISP and maize marketing via FRA hold a substantial portion, accounting for 30-70% of GRZ's agricultural budget between 2013 and 2017 (Chapoto et al., 2016). We incorporate the proximity to FRA buying points in our analyses, considering the potential impact of election results on FRA's maize marketing activities in specific constituencies, similar to the hypothesized impact on FISP allocation (Mason, Jayne, and van de Walle, 2017). There exist other policies, such as the Food Security Pack Programme, which may have been affected by election results. However, their scale and scope are not comparable to those of FISP (or FRA).[12] Although it is not feasible to directly test the exogeneity of the instruments, we test for the overidentifying restrictions, and the results (discussed below) support the instruments' validity.

1.5 Results and Discussion

A pooled, unbalanced panel dataset was used to estimate the models. Standard errors are clustered at the household level and are robust to heteroskedasticity and serial correlation (Wooldridge, 2013). The Davidson-MacKinnon test was conducted to assess the exogeneity of

[12] The Food Security Pack Programme stands as one of GRZ's ISPs, operating alongside the FISP. This program focuses on assisting the most vulnerable farmers who are unable to purchase fertilizer, thereby not requiring any farmer contribution. In addition, GRZ facilitates fertilizer provision through the Expanded Food Security Pack and the Mother and Child Health Food Security Pack. Nevertheless, the data from the RALS 2019 indicates that less than 1% of farmers secured fertilizer through these three channels (Chapoto and Subakanya, 2019).

FISP fertilizer to the dependent variables. We report FE-IV estimation results when exogeneity is rejected and both FE and FE-IV results when exogeneity cannot be rejected. First-stage estimation results and the Sargan-Hansen test of overidentifying restrictions can be found in Appendix B, Tables 1.8 through 1.10.

Effects on Crop Production Diversity

Table 1.2 presents the FE-IV estimated results of the impact of FISP fertilizer on the field crop SID. Exogeneity of FISP fertilizer to SID is rejected at the 1 percent significance level, while we find no evidence of weak instruments. Additionally, the null hypothesis that the IVs are valid is not rejected at the 10 percent level.

The results indicate that FISP fertilizer has a negative effect on crop production diversity. Households that received FISP fertilizer, on average, exhibit a 0.22 lower SID compared to households without FISP fertilizer. Given the average field crop SID of approximately 0.43 in the sample, this represents a significant 51% reduction. Receiving an additional 200 kg of FISP fertilizer, corresponding to the standard package per beneficiary farmer, is related to a 0.14 decrease in SID. This finding corroborates the adverse link between FISP fertilizer and the SID, but it suggests a smaller effect than implied by the binary FISP fertilizer receipt results. It is likely that FISP fertilizer, primarily targeted at maize, prompted beneficiary households to allocate more of their field cropped area to maize cultivation at the cost of other crops. Supplementary findings using the Herfindahl index indicate that FISP increases the index, implying a higher concentration of area share in the FISP target crop (i.e., maize) and lower evenness across other crops (Appendix B, Table 1.11). Indeed, FISP beneficiary households, on average, allocate a higher proportion of their field crop area to maize than non-beneficiary households (Appendix B, Table 1.12). Similar patterns have been noted in previous studies for

Zambia, where input subsidies have been found to adversely affect crop production diversity (Mofya-Mukuka and Hichaambwa, 2018; Saenz and Thompson, 2017), discourage intercropping of maize alongside other crops, and promote continuous maize cropping on the same plot over an extended period (Morgan et al., 2019).

Effects on Household Income

The effects of FISP fertilizer on household net income, net farm income, and net off-farm income are presented in Table 1.3. Our analysis reveals a negative influence of FISP fertilizer on household net income, contrasting with the findings of Mason and Smale (2013) and Mason and Tembo (2015), who reported a modest increase in household income due to input subsidies in Zambia using data predating 2012. Using more recent data spanning the 2013/14 and 2017/18 agricultural years, we find that, on average, beneficiary households earned 57,000 ZMW *less* income than non-beneficiary households, *ceteris paribus*; this is largely attributable to FISP fertilizer's adverse effect on net farm income.[13] Net farm income is further decomposed into its two components: the gross value of agricultural production and total fertilizer cost. While the receipt of FISP fertilizers increases the total quantity of fertilizer used (Appendix B, Table 1.13), it does not appear to have a statistically significant impact on total fertilizer cost (Table 1.4, columns 3 to 5). This may be because FISP fertilizers are provided at subsidized prices, allowing beneficiary households to use more fertilizers without incurring significantly higher fertilizer expenses.

The negative impact of FISP fertilizer on net farm income appears to be driven by its adverse effects on the gross value of agricultural production (Table 1.4, columns 1 to 2). Despite

[13] Results for income variables that have not been winsorized are presented in Appendix B, Table 1.15. Additionally, upon examining the logarithm of net income as the outcome variable, we find that FISP fertilizer does not have a statistically significant effect on it.

increased access to and use of fertilizers among beneficiary households, the lower value of production may be attributed to several factors. One plausible explanation is the observed low crop yield response to fertilizer in Zambia, possibly due to the persistence of conventional, one-size-fits-all fertilizer guidelines and applications that do not consider the spatial variability of soil characteristics, such as soil organic matter or acidity (Burke et al., 2019; Chapoto, Chabala, and Lungu, 2016). Although hybrid maize seeds are expected to be more responsive to fertilizers in terms of yield compared to traditional varieties, the focus of smallholders on fertilizers and the variable yield performance of hybrid seeds have limited yield improvements (Waldman et al., 2017). In addition, the late delivery of FISP fertilizer might have further hindered its effectiveness in enhancing yields (Xu et al., 2009b).

Another possible reason is the limited agricultural diversification by beneficiary households. Beneficiary households tend to focus on maize production compared to non-beneficiary households, as revealed by the analyses of field crop SID and maize share of cropped area. Indeed, when disaggregating the gross value of agricultural production into maize and non-maize components, FISP fertilizer does not have a statistically significant effect on the gross value of maize production (more details in Appendix B, Table 1.14). However, it significantly reduces the gross value of non-maize agricultural production. This suggests that the program's focus on maize cultivation may incentivize beneficiary households to allocate resources primarily to maize, potentially at the expense of income that could have been earned through other agricultural production, such as the cultivation of high-value or cash crops. Consequently, this shift contributes to a reduction in the gross value of agricultural production and net income for these households.

Overall Effects on Household Dietary Diversity

Table 1.5 presents the results for the effects of FISP fertilizer on HDDS. We find that receiving FISP fertilizer is associated with a statistically significant decrease in HDDS, with an average reduction of 3.8 units. For each additional kilogram of FISP fertilizer received, there is a corresponding decrease of 0.01 units in HDDS.[14] The average HDDS in our sample is approximately 6, hence, the 3.8-unit decrease represents a substantial 63% reduction in HDDS compared to the sample mean.

This pronounced negative association between FISP fertilizer and HDDS can be explained through the two underlying pathways. Firstly, FISP fertilizer had an adverse effect on crop production diversification. Subsidized maize fertilizers encourage households to shift toward more maize-centric farming, resulting in a reduced variety of crops grown on their farms. Consequently, there are fewer diverse food options available for household consumption from own production. This aligns with the findings of Mofya-Mukuka and Hichaambwa (2018), who found a positive association between crop diversification and HDDS in the Zambian context.

Secondly, FISP fertilizer had a detrimental impact on household net income. Beneficiary households tend to prioritize maize production, often at the expense of income-generating opportunities from non-maize agricultural production, such as high-value or cash crops. Cultivating a diverse range of crops may also serve as a buffer against shocks from factors like low seasonal rainfall or a drop in maize market prices. Indeed, Mofya-Mukuka and Hichaambwa

[14] Given that HDDS is a count variable, we conducted a Poisson regression that accounts for both household fixed effects and the endogeneity of FISP fertilizer. Following the approach outlined by Lin and Wooldridge (2019), we first estimated the reduced form of FISP fertilizer kg (first stage) and obtained FE residuals. Subsequently, we implemented an FE Poisson regression with corrected standard errors. Our findings from this regression are consistent with previous results, showing a negative relationship between the amount of FISP fertilizer and HDDS. However, this relationship appears less pronounced, with each additional kilogram of FISP fertilizer linked to a 0.001 unit decrease in HDDS. This regression was specifically conducted for the FISP fertilizer amount, treated as a continuous variable, thus justifying the correction of standard errors.

(2018) found a positive association between crop diversification and household farm income in Zambia. The resulting income reduction induced by FISP may lead households to cut back on purchasing diverse foods.

Our finding of an adverse effect of FISP on HDDS contradicts previous studies in Zambia. Kuntashula and Mwelwa-Zgambo (2022), relying on cross-sectional data from the 2013/14 agricultural year, suggest a positive influence of FISP on HDDS. This discrepancy can primarily be attributed to differences in data and empirical methodologies. We use panel data spanning the 2013/14 and 2017/18 agricultural years. The dynamics of FISP effects on HDDS may have unfolded differently over this extended period, especially with the nationwide implementation of the new e-Voucher system in 2017/18. Moreover, our adoption of an FE-IV strategy allows for the control of both time-invariant and time-varying household-specific unobservable factors, preventing potential overestimation of the effect of FISP on HDDS. This approach also differs from Tossou and Baylis (2018), who adopt an FE approach using a smaller dataset than RALS but focus on the transition from conventional FISP to the e-Voucher FISP.

Limitations

The study's limitations primarily stem from the limited availability of data and IVs for FISP participation. Firstly, our analyses provide a partial estimate of FISP's effects. Although FISP predominantly distributed fertilizer, measuring FISP participation solely based on fertilizer acquisition does not capture the program's comprehensive impact. Furthermore, we did not directly account for the potential adverse effects of delayed FISP fertilizer deliveries, which could reduce fertilizer efficiency and result in production losses (Chapoto et al., 2016), subsequently affecting household dietary diversity. Secondly, the interconnected nature of households' decisions regarding crop production diversity, income, and dietary diversity would benefit from being evaluated simultaneously. Estimating a system of simultaneous equations would help determine whether production diversity or income has a greater effect on dietary diversity. However, the absence of IVs to address the potential endogeneity of production diversity and household income to HDDS precluded a structural analysis similar to that conducted by Bellon, Ntandou-Bouzitou, and Caracciolo (2016). Lastly, the intrahousehold impacts of FISP fertilizer were not explored. Detailed insights into dietary diversity and quality can be gained through measures such as the Women's dietary diversity score and the Minimum dietary diversity for women of reproductive age (Verger et al., 2019); however, our dataset lacked individual-level dietary diversity information. Given the potential intrahousehold issues stemming from the allocation and use of subsidized inputs (Chirwa et al., 2011), coupled with the heightened risk from insufficient dietary diversity among women of reproductive age (Smale, Thériault, and Mason, 2020), there is a critical need for future research to examine the intrahousehold dietary diversity impacts of input subsidies within the Zambian context.

1.6 Conclusions and Policy Implications

This study investigates the impacts of agricultural input subsidies on household dietary diversity and its underlying pathways, namely the production diversity pathway and the income pathway. Using data from two waves (2015 and 2019) of a nationally representative smallholder household panel survey in Zambia, we estimate the effects of fertilizer received through the Zambian Farmer Input Support Programme on several key variables: the Simpson index of diversification for field crops, household net income, and the household dietary diversity score. Our contributions to the existing literature on input subsidy programs lie in providing compelling evidence of their unintended effects and the underlying pathways using a robust empirical strategy. To address endogeneity concerns arising from self-selection into ISPs, we employ the

FE-IV estimation method, using locality election variables as instruments for program participation.

Findings indicate that fertilizer acquired through the Zambian FISP negatively affects household crop production diversification, prompting beneficiary households to allocate a larger proportion of their cropped land to maize. This unintended effect is consistent with the findings of Morgan et al. (2019). Further, we find that FISP fertilizer adversely affects household net income by reducing the gross value of agricultural production, particularly in non-maize crops. FISP beneficiary households, concentrating on maize cultivation, experience lower values in gross non-maize agricultural production and net farm income compared to non-beneficiary households. This aligns with the positive relationship between crop diversification and household farm income in Zambia (Mofya-Mukuka and Hichaambwa, 2018), suggesting that the unintended effects of FISP on crop diversity may influence the income pathway as well.

Overall, FISP fertilizer is linked to reduced HDDS, stemming from lower crop diversity on farms and decreased household income restricting food purchasing. Our study highlights that ISPs, as implemented in Zambia, can have unintended adverse effects on production diversification, household income, and food security outcomes, despite their goal of improving smallholders' incomes and food security. It also underscores the importance of understanding how subsidized staple crop fertilizers influence intermediate determinants (i.e., crop production diversity and household income) that ultimately affect dietary diversity among smallholder farm households. Such information is crucial for more tailored and effective program design, implementation, and evaluation.

Additionally, it is worth noting that despite the negative impact of FISP on crop production diversity and household net income, there is potential for improvement. The positive relationship observed between the years of e-Voucher FISP implementation and field crop SID, as well as household net income (Tables 1.2 and 1.3), suggests that efforts to tailor the e-Voucher program and promote diverse input distribution may enhance production diversity and income in the future. Such improvements could contribute to enhanced household dietary diversity. A valuable area for future research involves evaluating the impact of the e-Voucher program in facilitating the distribution and use of diverse agricultural inputs and assessing its effects on smallholder cropping patterns, socio-economic outcomes, and food security measures. This examination will provide critical insights for shaping future agricultural policies and interventions.

REFERENCES

Ahmad, S., M. Smale, V. Thériault, and E. Maiga. 2022. "Input subsidies and crop diversity on family farms in Burkina Faso." *Journal of Agricultural Economics* 00:1-18.

Angrist, J. D., and J.-S. Pischke. 2008. *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Arimond, M., D. Wiesmann, E. Becquey, A. Carriquiry, M.C. Daniels, M. Deitchler, N. Fanou-Fogny, M.L. Joseph, G. Kennedy, Y. Martin-Prevel, and L.E. Torheim. 2010. "Simple food group diversity indicators predict micronutrient adequacy of women's diets in 5 diverse, resource-poor settings." *The Journal of nutrition* 140(11):2059S-2069S.

Arndt, C., K. Pauw, and J. Thurlow. 2016. "The Economy-wide Impacts and Risks of Malawi's Farm Input Subsidy Program" *American Journal of Agricultural Economics* 98 (3):962-980.

Assima, A., G. Zanello, and M. Smale. 2022. "Articulating fertilizer subsidy effects on women's diet quality by food supply source in Mali." *CABI Agriculture and Bioscience* 3(1): 42.

Bellon, M.R., G.D. Ntandou-Bouzitou, and F. Caracciolo. 2016. "On-farm diversity and market participation are positively associated with dietary diversity of rural mothers in Southern Benin, West Africa." *PLOS ONE* 11(9):e0162535.

Bellon, M.R., B.H. Kotu, C. Azzarri, and F. Caracciolo. 2020. "To diversify or not to diversify, that is the question. Pursuing agricultural development for smallholder farmers in marginal areas of Ghana." *World Development* 125:104682.

Burke, W.J., E. Frossard, S. Kabwe, and T.S. Jayne. 2019. "Understanding fertilizer adoption and effectiveness on maize in Zambia." *Food Policy* 86:101721.

Chakrabarti, A., A.P. Harou, J. Fanzo, and C.A. Palm. 2024. "Exploring agriculture-child nutrition pathways: Evidence from Malawi's Farm Input Subsidy Program." *Food Security* 16:201-221.

Chapoto, A., L.M. Chabala, and O.N. Lungu. 2016. "A Long History of low productivity in Zambia: Is it time to do away with blanket recommendations?" *Zambia Social Science Journal* 6(2):46-79.

Chapoto, A., R. Mofya-Mukuka, T. Namonje-Kapembwa, O. Zulu-Mbata, and B. Chisanga. 2016. "Achieving More with Less: Reform and Scaling Down of Food Reserve Agency and Farmer Input Support Programme and Boosting Social Protection." *Zambia Social Science Journal* 6(2): Article 5.

Chapoto, A. and O. Zulu-Mbata. 2016. *Rural Agricultural Livelihoods Survey 2015 Survey Report.* Indaba Agricultural Policy Research Institute (IAPRI), Lusaka, Zambia.

Chapoto, A., and M. Subakanya. 2019. *Rural Agricultural Livelihoods Survey 2019 Report*. IAPRI, Lusaka, Zambia.

Chibwana, C., M. Fisher, and G. Shively. 2012. "Cropland allocation effects of agricultural input subsidies in Malawi." *World Development* 40(1):124-133.

Chirwa, E.W., M.M. Matita, P. M. Mvula, and A. Dorward. 2013. "Repeated Access and Impacts of the Farm Input Subsidy Programme in Malawi: Any Prospects of Graduation?" Working paper No. 65., Future Agricultures Consortium, University of Sussex, Brighton, England.

Chirwa, E.W., P.M. Mvula, A. Dorward, and M. Matita. 2011. "Gender and intra-household use of fertilizers in the Malawi farm input subsidy programme." Working paper 28, Brighton: Future Agricultures Consortium, Brighton, United Kingdom.

Dillon, A., K. McGee, and G. Oseni. 2015. "Agricultural Production, Dietary Diversity and Climate Variability." *The Journal of Development Studies* 51(8):976-995.

Ebenezer, M. 2022. "Urban Household Food Security: An Assessment of the Correlates of Micronutrient-Sensitive Dietary Diversity." *Journal of Developing Areas* 56(2).

Farnworth, C.R. 2010. Gender aware approaches in agricultural programmes: A study of Sida-supported agricultural programmes. Sida Evaluation 2010:3, The Swedish International Development Cooperation Agency (Sida).

Fujimoto, T., and A. Suzuki. 2021. "Do fertilizer and seed subsidies strengthen farmers' market participation? The impact of Tanzania NAIVS on farmers' purchase of agricultural inputs and their maize-selling activities." Paper presented at International Conference of Agricultural Economists 2021, 17–31 August.

Gignoux, J., K. Macours, D. Stein, and K. Wright, K. 2022. "Input subsidies, credit constraints, and expectations of future transfers: Evidence from Haiti." *American Journal of Agricultural Economics* 1-27.

Gilligan, D.O., J. Hoddinott, and A.S. Taffesse. 2009. "The impact of Ethiopia's productive safety net programme and its linkages." *Journal of Development Studies* 45(10):1684-1706.

Gine, X., S. Patel, C. Cuellar-Martinez, S. McCoy, and R. Lauren. 2015. Enhancing food production and food security through improved inputs: An evaluation of Tanzania's national agricultural input voucher scheme with a focus on gender impacts. 3ie impact evaluation report 23. New Delhi: International Initiative for Impact Evaluation.

Habtemariam, L. T., C. Gornott, H. Hoffmann, and S. Sieber. 2021. "Farm production diversity and household dietary diversity: panel data evidence from rural households in Tanzania." *Frontiers in Sustainable Food Systems* 5:151.

Haddad, L., E. Achadi, M.A. Bendech, A. Ahuja, K. Bhatia, Z. Bhutta, M. Blössner, E. Borghi, E. Colecraft, M. de Onis, K. Eriksen, J. Fanzo, R. Flores-Ayala, P. Fracassi, E. Kimani-Murage, E.N. Koukoubou, J. Krasevec, H. Newby, R. Nugent, S. Oenema, Y. Martin-Prével, J. Randel, J. Requejo, T. Shyam, E. Udomkesmalee, and K.S. Reddy. 2015. "The Global Nutrition Report 2014: Actions and Accountability to Accelerate the World's Progress on Nutrition." *The Journal of Nutrition* 145(4):663-671.

Harou, A. P. (2018). "Unraveling the effect of targeted input subsidies on dietary diversity in household consumption and child nutrition: The case of Malawi." *World Development* 106:124-135.

Hill, M.O. 1973. "Diversity and evenness: a unifying notation and its consequences." Ecology 54(2):427-432.

Hoddinott, J. and Y. Yohannes. 2002. "Dietary Diversity as a Food Security Indicator." Food Consumption and Nutrition Division Discussion Paper No. 136., International Food Policy Research Institute, Washington, DC.

Holden, S. T. 2019. "Economics of farm input subsidies in Africa." *Annual Review of Resource Economics* 11:501-522.

Holden, S., and R. Lunduka. 2013. "Who benefits from Malawi's targeted farm input subsidy program?" *Forum for Development Studies* 40(1):1-25.

Ickowitz, A., B. Powell, D. Rowland, A. Jones, and T. Sunderland. 2019. "Agricultural intensification, dietary diversity, and markets in the global food security narrative." *Global Food Security* 20:9-16.

Jayne, T.S., N.M. Mason, W.J. Burke, and J. Ariga. 2018. "Review: Taking stock of Africa's second-generation agricultural input subsidy programs." *Food Policy* 75:1-14.

Jayne, T.S., D. Mather, N. Mason, and J. Ricker-Gilbert. 2013. "How do fertilizer subsidy programs affect total fertilizer use in sub-Saharan Africa? Crowding out, diversion, and benefit/cost assessments." *Agricultural Economics* 44:687-703.

Jayne, T.S., and S. Rashid. 2013. "Input subsidy programs in sub-Saharan Africa: a synthesis of recent evidence." *Agricultural Economics* 44:547-562.

Jones, A.D. 2017. "Critical review of the emerging research evidence on agricultural biodiversity, diet diversity, and nutritional status in low-and middle-income countries." *Nutrition Reviews* 75(10):769-782.

Joshi, P.K., A. Gulati, P.S. Birthal, and L. Tewari. 2004. "Agriculture diversification in South Asia: patterns, determinants and policy implications." *Economic and political weekly* 39(24): 2457-2467.

Kahenge, Z., K. Muendo, and N. Nhamo. 2019. “Factors Influencing Crop Commercialization Among Soybeans Smallholder Farmers in Chipata District, Eastern Zambia.” *Journal of Agriculture, Science and Technology* 19(1):13-31.

Kankwamba, H., M. Mapila, and K. Pauw. 2012. Determinants and spatiotemporal dimensions of crop diversification in Malawi. Project Report produced under a co-financed research agreement between Irish Aid, USAID and IFPRI. Paper No. 2.

Kanter, R., H.L. Walls, M. Tak, F. Roberts, and J. Waage. 2015. “A conceptual framework for understanding the impacts of agriculture and food system policies on nutrition and health.” *Food Security* 7(4):767-777.

Karamba, R.W. 2013. “Input Subsidies and their Effect on Cropland Allocation, Agricultural Productivity, and Child Nutrition: Evidence from Malawi.” PhD dissertation, American University.

Karamba, R.W., and P.C. Winters. 2015. “Gender and agricultural productivity: implications of the Farm Input Subsidy Program in Malawi.” *Agricultural Economics* 46(3):357-374.

Kennedy, G., A. Berardo, C. Papavero, P. Horjus, T. Ballard, M. Dop, J. Delbaere, and I. Brouwer. 2010. “Proxy measures of household food consumption for food security assessment and surveillance: Comparison of the household dietary diversity and food consumption scores.” *Public Health Nutrition* 13(12):2010-2018.

Kijima, Y. 2022. “Effect of Nigeria’s e-voucher input subsidy program on fertilizer use, rice production, and household income.” *Food Security* 14(4):919-935.

Kilic, T., C. Carletto, J. Miluka, and S. Savastano. 2009. “Rural Nonfarm Income and its Impact on Agriculture: Evidence from Albania.” *Agricultural Economics* 40(2):139-160.

Kuntashula, E., and L. Mwelwa-Zgambo. 2022. “Impact of the farmer input support policy on agricultural production diversity and dietary diversity in Zambia.” *Food Policy* 102329.

Leroy, J.L., M. Ruel, E.A. Frongillo, J. Harris, and T.J. Ballard. 2015. “Measuring the Food Access Dimension of Food Security: A Critical Review and Mapping of Indicators.” *Food and Nutrition Bulletin* 36(2):167-195.

Lin, W. and J.M. Wooldridge. 2019. “Testing and correcting for endogeneity in nonlinear unobserved effects models.” In *Panel data econometrics*, Academic Press, pp. 21-43.

Magurran, A. 1991. *Ecological Diversity and Its Measurement*. Princeton: Princeton University Press.

Mason, N.M., T.S. Jayne, and R. Mofya-Mukuka. 2013. “Zambia’s input subsidy programs.” *Agricultural Economics* 44:613-628.

Mason, N.M., A. Kuteya, H. Ngoma, D.A. Tossou, and K.R. Baylis. 2020. “Does shifting to a flexible e-voucher approach improve input subsidy program outcomes? Quasi-experimental evidence from Zambia’s crop forecast surveys.” Research Paper No. 165, Feed the Future Innovation Lab for Food Security Policy (FSP), Michigan State University.

Mason, N.M., and J. Ricker-Gilbert. 2013. “Disrupting Demand for Commercial Seed: Input Subsidies in Malawi and Zambia.” *World Development* 45:75-91.

Mason, N.M., and M. Smale. 2013. “Impacts of subsidized Hybrid seed on indicators of economic well-being among smallholder maize growers in Zambia.” *Agricultural Economics* 44(6):659-670.

Mason, N.M., and S.T. Tembo. 2015. “Do input subsidy programs raise incomes and reduce poverty among smallholder farm households? Evidence from Zambia.” Working Paper No. 92, Indaba Agricultural Policy Research Institute, Lusaka, Zambia.

Mason, N.M., T.S. Jayne, and R. Mofya-Mukuka. 2013. “Zambia’s input subsidy programs.” *Agricultural Economics* 44:613-628.

Mason, N. M., T.S. Jayne, and N. van de Walle. 2017. “The political economy of fertilizer subsidy programs in Africa: Evidence from Zambia.” *American Journal of Agricultural Economics* 99(3):705-731.

Mason, N.M., A. Wineman, L. Kirimi, and D. Mather. 2017. “The effects of Kenya’s ‘Smarter’ input subsidy program on smallholder behavior and incomes: do different quasi-experimental approaches lead to the same conclusions?” *Journal of Agricultural Economics* 68(1):45-69.

Matita, M., L. Chiwaula, E.W. Chirwa, J. Mazalale, and H. Walls. 2022. “Subsidizing improved legume seeds for increased household dietary diversity: Evidence from Malawi’s Farm Input Subsidy Programme with implications for addressing malnutrition in all its forms.” *Food Policy* 113: 102309.

Meng, E.C.H., M. Smale, M. Bellon, and D. Grimanelli. 1998. “Definition and measurement of crop diversity for economic analysis.” In M. Smale, ed. *Farmers Gene Banks and Crop Breeding: Economic Analyses of Diversity in Wheat Maize and Rice*. Dordrecht: Springer Netherlands, pp. 19-32.

Ministry of Agriculture (MoA), Republic of Zambia. Electronic Voucher Implementation Manual for the 2016/2017 Agricultural Season Farmer Input Support Programme. MoA, Lusaka, Zambia.

——. Implementation Manual for the 2018/2019 Agricultural Season Farmer Input Support Programme (Version 1). MoA, Lusaka, Zambia.

——. Farmer Input Support Programme 2023/24 Direct Input Supply & Electronic Voucher Implementation Handbook. MoA, Lusaka, Zambia.

Ministry of Agriculture and Livestock (MAL), Republic of Zambia. Implementation Manual for the 2014/15 Agricultural Season Farmer Input Support Programme. MAL, Lusaka, Zambia.

——. Electronic Voucher Implementation Manual for the 2015/16 Agricultural Season Farmer Input Support Programme. MAL, Lusaka, Zambia.

Mofya-Mukuka, R., and M. Hichaambwa. 2018. "Livelihood effects of crop diversification: a penal data analysis of rural farm households in Zambia." *Food Security* 10:1449-1462.

Mofya-Mukuka, R., and F. Singogo. 2020. *2020 Zambia Food Security and Nutrition Report.* IAPRI, Lusaka, Zambia.

Morgan, S. N., N. M. Mason, N. K. Levine, and O. Zulu-Mbata. 2019. "Dis-incentivizing sustainable intensification? The case of Zambia's maize-fertilizer subsidy program." *World Development* 122:54-69.

Mulenga, B.P., H. Ngoma, and C. Nkonde. 2021. "Produce to eat or sell: Panel data structural equation modeling of market participation and food dietary diversity in Zambia." *Food Policy* 102:102035.

Muthini, D., J. Nzuma, and R. Nyikal. 2020. "Farm production diversity and its association with dietary diversity in Kenya." *Food Security* 12:1107-1120.

Nandi, R., S. Nedumaran, and P. Ravula. 2021. "The interplay between food market access and farm household dietary diversity in low and middle income countries: A systematic review of literature." *Global Food Security* 28:102-127.

Nkonde, C., K. Audain, R.N. Kiwanuka-Lubinda, and P. Marinda. 2021. "Effect of agricultural diversification on dietary diversity in rural households with children under 5 years of age in Zambia." *Food Science & Nutrition* 9(11):6274-6285.

Novignon, J., G.C. Chirwa, and R.B. Frempong. 2020. "Impact of Agricultural Input Subsidy on Nutritional Outcomes in Malawi" Working Paper No. 005. African Economic Research Consortium, Nairobi, Kenya.

Pelletier, J., H. Ngoma, N.M. Mason, and C.B. Barrett. 2020. "Does smallholder maize intensification reduce deforestation? Evidence from Zambia." *Global Environmental Change* 63:100484.

Pinstrup-Andersen, P. 2013. "Can Agriculture Meet Future Nutrition Challenges?" *European Journal of Development Research* 25:5-12.

Pope, R.D., and R. Prescott. 1980. "Diversification in relation to farm size and other socioeconomic characteristics." *American Journal of Agricultural Economics* 62(3):554-559.

Rhoades, S.A. 1993. "The Herfindahl-Hirschman index." Fed. Res. Bull. No.79, March.

Rehima, M., K. Belay, A. Dawit, and S. Rashid. 2013. "Factors affecting farmers' crops diversification: Evidence from SNNPR, Ethiopia." *International Journal of Agricultural Sciences* 3(6):558-565.

Ricker-Gilbert, J., T. Jayne, and G. Shively. 2013. "Addressing the "wicked problem" of input subsidy programs in Africa." *Applied Economic Perspectives and Policy* 35(2):322-340.

Ricker-Gilbert, J., N.M. Mason, F.A. Darko, and S.T. Tembo. 2013. "What are the effects of input subsidy programs on maize prices? Evidence from Malawi and Zambia." *Agricultural Economics* 44:671-686.

Ruel, M. T., J. Harris, and K. Cunningham. 2013. "Diet quality in developing countries." In V. R. Preedy, L.-A. Hunter, and V. B. Patel, ed. Diet quality. New York: Springer New York, pp. 239-261.

Sadoulet, E., and A. de Janvry. 1995. *Quantitative Development Policy Analysis*. Johns Hopkins University Press, Baltimore, MD.

Saenz, M., and E. Thompson. 2017. "Gender and policy roles in farm household diversification in Zambia." *World Development* 89:152-169.

Saha, A. 1994. "A two-season agricultural household model of output and price uncertainty." *Journal of Development Economics* 45(2):245-269.

Shitumbanuma, V., P. Simfukwe, D. Kalala, B. Kaninga, B. Gondwe, M. Nambala, S. Kabwe, G. Siulemba, N. Kapulu, O. Lungu, and J. Mutegi. 2015. *Integrated soil fertility management in Zambia*. Zambia Soil Health Consortium, Chilanga, Zambia.

Sibande, L., A. Bailey, and S. Davidova. 2017. "The impact of farm input subsidies on maize marketing in Malawi." *Food Policy* 69:190-206.

Sibhatu, K.T., and M. Qaim. 2018. "Meta-analysis of the association between production diversity, diets, and nutrition in smallholder farm households." *Food Policy* 77:1-18.

Sichoongwe, K., L. Mapemba, D. Ng'ong'ola, and G. Tembo. 2014. The Determinants and Extent of Crop Diversification among Smallholder Farmers: A Case Study of Southern Province, Zambia. IFPRI Working paper No. 05, International Food Policy Research Institute, Washington, DC.

Singh, I., L. Squire, and J. Strauss. 1986. *Agricultural Household Models: Extensions,* *Applications and Policy*. Johns Hopkins University Press, Baltimore, MD.

Sinyolo, S., C. Murendo, A.M. Nyamwanza, S.A. Sinyolo, C. Ndinda, and C.O. Nwosu. 2021 "Farm production diversification and dietary diversity among subsistence farming households: panel data evidence from South Africa." *Sustainability* 13(18):10325.

Simtowe, F., and H. De Groote. 2021. "Seasonal participation in maize markets in Zambia: Do agricultural input subsidies and gender matter?" *Food Security* 13:141-155.

Smale, M., ed. 2006. *Valuing crop biodiversity: on-farm genetic resources and economic change*. CABI Publishing.

Smale, M., M. Moursi, and E. Birol. 2015. "How does adopting hybrid maize affect dietary diversity on family farms? Micro-evidence from Zambia." *Food Policy* 52:44-53.

Smale, M., and V. Thériault. 2022. "Input subsidy effects on crops grown by smallholder farm women: The example of cowpea in Mali." *Oxford Development Studies* 50(3): 244-258.

Smale, M., V. Thériault, and N.M. Mason. 2020. "Does subsidizing fertilizer contribute to the diet quality of farm women? Evidence from rural Mali." *Food Security* 12:1407-1424.

Snapp, S.S. and M. Fisher. 2015. ""Filling the maize basket" supports crop diversity and quality of household diet in Malawi." *Food Security* 7:83-96.

Swindale, A. and P. Bilinsky. 2006. *Household Dietary Diversity Score (HDDS) for Measurement of Household Food Access: Indicator Guide (Version 2)*. Food and Nutrition Technical Assistance (FANTA) Project, Academy for Educational Development, Washington, D.C.

——. 2010. *Months of Adequate Household Food Provisioning (MAHFP) for Measurement of Household Food Access: Indicator Guide (Version 4)*. FANTA Project, Academy for Educational Development, Washington, D.C.

Takeshima, H., and L.S.O. Liverpool-Tasie. 2015. "Fertilizer subsidies, political influence and local food prices in Sub-Saharan Africa: evidence from Nigeria." *Food Policy* 54:11-24.

Thériault, V. and M. Smale. 2021. "The unintended consequences of the fertilizer subsidy program on crop species diversity in Mali." *Food Policy* 102:102121.

Thériault, V., M. Smale, and H. Haider. 2018. "Economic incentives to use fertilizer on maize under differing agro-ecological conditions in Burkina Faso." *Food Security* 10(5):1263-1277.

Tossou, D.A., and K. R. Baylis. 2018. "Does Flexibility in Agricultural Input Subsidy Programs Improve Smallholder Crop Yields and Household Food Security? Evidence from Zambia." Paper presented at AAEA annual meeting, Washington, D.C., 5–7 August.

Van Dusen, M.E. and J.E. Taylor. 2005. "Missing markets and crop biodiversity: evidence from Mexico." *Environment and Development Economics* 10 (4):513-531.

Verger, E.O., C. Gaillard, A.D. Jones, R. Remans, and G. Kennedy. 2021. "Construction and Interpretation of Production and Market Metrics Used to Understand Relationships with Dietary Diversity of Rural Smallholder Farming Households." *Agriculture* 11:749.

Verger, E.O., T.J. Ballard, M.C. Dop, and Y. Martin-Prevel. 2019. "Systematic review of use and interpretation of dietary diversity indicators in nutrition-sensitive agriculture literature." *Global Food Security* 20:156-169.

Vijayalaxmi, D. K., K.B. Umesh, and V. Saravanakumar. 2020. "Interlinking dietary diversity, production diversity, and climate change: Non-separable farm household model approach." *Agricultural Economics Research Review* 33:25-38.

Waldman, K.B., J.P. Blekking, S.Z. Attari, and T.P. Evans. 2017. "Maize seed choice and perceptions of climate variability among smallholder farmers." *Global environmental change* 47:51-63.

Wooldridge, J. M. 2010. *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.

Wooldridge, J. M. 2013. *Introductory Econometrics: A Modern Approach*. 5th ed. Mason, OH: South-Western.

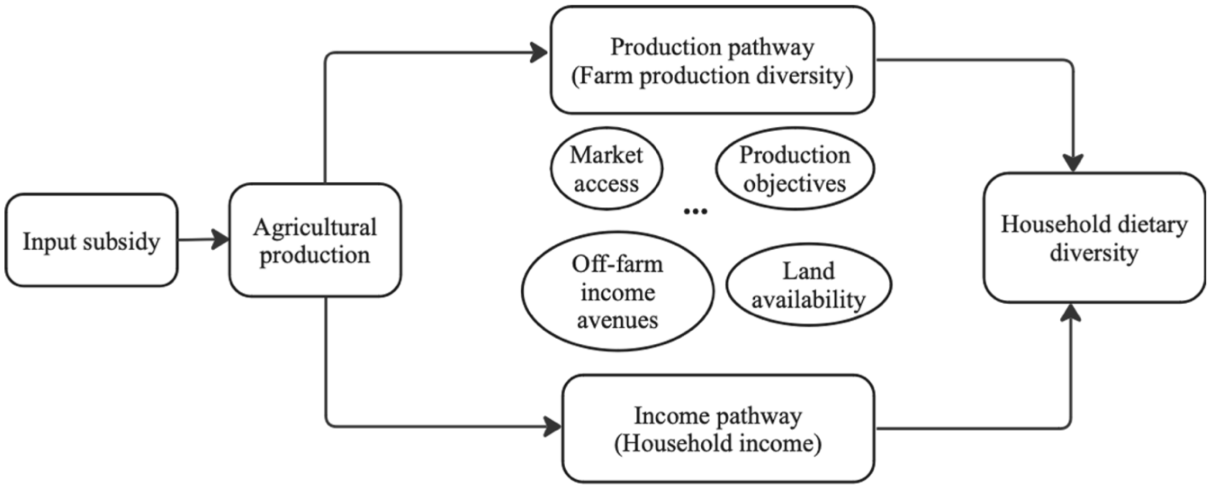
Wossen, T., T. Abdoulaye, A. Alene, S. Feleke, J. Ricker-Gilbert, V. Manyong, and B.A. Awotide. 2017. "Productivity and Welfare Effects of Nigeria's e-Voucher-Based Input Subsidy Program." *World Development* 97:251-265.

Xu, Z., W.J. Burke, T.S. Jayne, and J. Govereh. 2009a. "Do input subsidy programs "crowd in" or "crowd out" commercial market development? Modeling fertilizer demand in a two-channel marketing system." *Agricultural Economics* 40:79-94.

Xu, Z., Z. Guan, T.S. Jayne, and R. Black. 2009b. "Factors influencing the profitability of fertilizer use on maize in Zambia." *Agricultural Economics* 40(4):437-446.

APPENDIX A. TABLES AND FIGURES

Figure 1.1 The linkages between input subsidies and household dietary diversity



Notes: Conceptual framework developed based on Kanter et al. (2015), Nandi, Nedumaran, and Ravula (2021), Novignon, Chirwa, and Frempong (2020), Snapp and Fisher (2015), and Smale, Thériault, and Mason (2020).

Figure 1.2 Timeline of the 2013/14 agricultural year

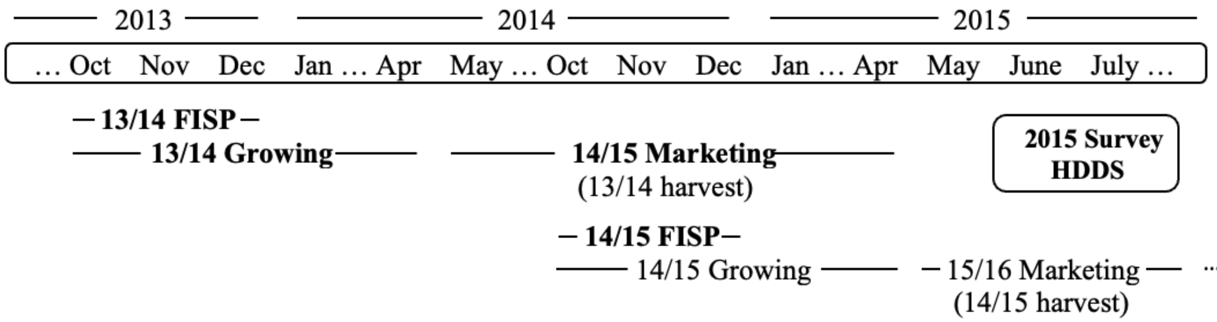


Table 1.1 Summary statistics

Variable	RALS 2015			RALS 2019		
	2013/14 Ag. year			2017/18 Ag. year		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Dependent variables						
HDDS	7,933	5.9	2.1	7,241	6.1	1.9
Field crop SID[15]	7,748	.4	.2	7,028	.5	.2
Net income (ZMW'1000)[16]	7,933	15.8	28.3	7,240	44.8	78.1
Net farm income (ZMW'1000)	7,933	7.9	14.6	7,240	37.9	64.6
Net off-farm income (ZMW'1000)	7,933	7.3	16.5	7,240	7.2	15.6
FISP fertilizer participation variables						
FISP fertilizer receipt (1=yes)	7,934	.4	.5	7,241	.4	.5
Kg of FISP fertilizer received	7,934	116.6	188.0	7,241	141.1	210.0
Instrumental variables						
Ruling party won parliament seat (1=yes) *	7,794	.4	.5	7,241	.5	.5
Absolute vote spread (% point)[17] **	7,746	36.4	17.8	7,103	38.5	23.8
Control variables						
Female-headed (1=yes)	7,934	.2	.4	7,241	.2	.4
Head's education (years)	7,926	6.0	3.7	7,241	6.0	3.7
Head's age (years)	7,934	48.7	14.8	7,241	52.0	14.3
FTAE	7,934	5.0	2.3	7,241	4.5	2.1
Value of productive assets (ZMW'1000)	7,934	26.5	256.9	7,241	30.9	418.2
Landholding size (ha)	7,934	4.7	10.5	7,241	5.4	15.6
Off-farm income share – *HDDS*	7,934	.4	.3	7,241	.4	.3
Basal fertilizer price (ZMW/kg) – *SID, HDDS*	7,934	4.3	.4	7,241	3.3	.4
Maize price (ZMW/kg)	7,934	1.2	.1	7,241	.9	.2
Years of e-Voucher FISP in household district	7,934	0	0	7,241	1.7	.7
Km to tarmac/tarred road	7,933	28.3	36.5	7,240	27.3	36.0
Km to agro-dealer – *SID, HDDS*	7,932	30.2	32.5	7,240	26.9	33.9
Km to marketplace	7,932	24.7	30.3	7,240	24.1	30.7
Km to FRA buying point (growing months) – *SID*	7,934	10.4	15.3	7,240	12.7	19.7
Km to FRA buying point (marketing months) – *Income, HDDS*	7,934	10.4	15.3	7,240	12.7	20.0
Growing months total rainfall (100mm)	7,934	10.1	2.7	7,241	10.5	2.2
Cell phone ownership (1=yes) – *Income, HDDS*	7,933	.6	.5	7,237	.7	.5
Plough ownership (1=yes) – *SID, HDDS*	7,933	.3	.4	7,241	.3	.5
Cooperative membership (1=yes) – *Income, HDDS*	7,934	.5	.5	7,241	.5	.5

Notes: All monetary values are in real 2014/15 ZMW. Different sets of control variables are included in different analyses based on their reference period and relevance to the dependent variables. *SID*, *Income*, and *HDDS* indicate inclusion in the field crop SID, income, and HDDS analyses, respectively. Variables without such indication are included in all three analyses. * The binary variable is assigned a value of 1 if the ruling party won a parliament seat in the household's constituency. ** Absolute vote spread is the absolute value of the vote share difference between the ruling and the leading opposition party in the household's constituency. See section 1.4 for details on the IVs.

[15] Households not involved in crop production were still considered farm households due to their engagement in producing vegetables, fruits, and/or raising livestock/fish.

[16] Income variables were winsorized at the 1% and 99% levels to mitigate the influence of outliers.

[17] Detailed vote share information was unavailable for some constituencies due to factors such as the deaths of candidates or the absence of a ruling party candidate.

Table 1.2 Effects of FISP fertilizer on crop production diversity (FE-IV)

	Field crop SID	
VARIABLES	(1)	(2)
FISP fertilizer receipt (1=yes)	-0.223**	–
	(0.101)	
FISP fertilizer kg	–	-0.0007**
		(0.0003)
Year (1=2019)	0.0171	0.0234
	(0.0204)	(0.0214)
Maize price (ZMW)	-0.0080	-0.0210
	(0.0295)	(0.0304)
Female head (1=yes)	-0.0625**	-0.0645**
	(0.0264)	(0.0271)
Head's education (years)	0.0010	0.0007
	(0.0023)	(0.0023)
Head's age (years)	0.0002	0.0002
	(0.0010)	(0.0011)
FTAE	0.0186***	0.0187***
	(0.0038)	(0.0038)
Value of productive assets (ZMW'1000)	-7.80e-06***	-6.65e-06**
	(2.91e-06)	(3.11e-06)
Landholding size (ha)	0.0002	0.0004
	(0.0003)	(0.0003)
Basal fertilizer price (ZMW)	-0.0187*	-0.0151
	(0.0105)	(0.0106)
Years of e-Voucher FISP implementation	0.0125	0.0175**
	(0.0079)	(0.0077)
Km to tarred road	-4.68e-06	-5.64e-05
	(0.0002)	(0.0002)
Km to agro-dealer	1.42e-05	4.07e-05
	(0.0002)	(0.0002)
Plough ownership (1=yes)	0.0375***	0.0519***
	(0.0140)	(0.0175)
Growing season rainfall (mm)	1.32e-05	2.51e-05
	(3.53e-05)	(3.72e-05)
Km to marketplace	0.0002	0.0001
	(0.0002)	(0.0002)
Km to FRA buying point	0.0001	8.87e-05
	(0.0002)	(0.0002)
Observations	12,930	12,930
Number of households	6,465	6,465
Davidson-MacKinnon test of exogeneity	9.529	8.363
	(Chi-sq(1) P-value=0.002)	(Chi-sq(1) P-value=0.004)

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.3 Effects of FISP fertilizer on net household incomes (ZMW'1000) (FE-IV)

	Net income		Net off-farm income[18]		Net farm income	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
FISP fertilizer receipt (1=yes)	-56.68*	–	3.923	–	-64.26**	–
	(31.51)		(6.498)		(28.65)	
FISP fertilizer kg	–	-0.176*	–	0.013	–	-0.203**
		(0.104)		(0.020)		(0.096)
Year (1=2019)	18.40***	19.00***	-0.628	-0.678	19.17***	19.87***
	(2.734)	(2.867)	(0.730)	(0.733)	(2.520)	(2.724)
Maize price	-1.846	-5.133	-1.656	-1.409	0.022	-3.757
	(4.782)	(4.914)	(1.273)	(1.272)	(4.602)	(4.856)
Female head	-11.20***	-11.97***	-0.815	-0.733	-11.11***	-12.06***
	(3.934)	(4.452)	(1.094)	(1.138)	(3.744)	(4.331)
Head's education (years)	0.717*	0.672	0.168*	0.173*	0.510	0.456
	(0.417)	(0.452)	(0.095)	(0.096)	(0.391)	(0.435)
Head's age (years)	0.233	0.257	0.018	0.016	0.217	0.245
	(0.155)	(0.168)	(0.042)	(0.043)	(0.136)	(0.153)
FTAE	1.104	1.189	0.368	0.358	0.627	0.732
	(0.862)	(0.903)	(0.243)	(0.249)	(0.788)	(0.842)
Value of productive assets (ZMW'1000)	0.005	0.005	0.001	0.001	0.004	0.004
	(0.005)	(0.005)	(0.001)	(0.001)	(0.005)	(0.005)
Landholding size (ha)	0.154**	0.182**	0.013	0.010	0.150**	0.183**
	(0.076)	(0.091)	(0.016)	(0.018)	(0.071)	(0.086)
Years of e-Voucher FISP	3.807**	4.983***	0.146	0.059	3.910**	5.258***
	(1.688)	(1.932)	(0.407)	(0.465)	(1.549)	(1.774)
Km to tarred road	-0.006	-0.015	-0.002	-0.002	-0.004	-0.014
	(0.026)	(0.027)	(0.005)	(0.005)	(0.025)	(0.026)
Cell phone ownership (1=yes)	-1.167	0.184	1.026***	0.921***	-2.379	-0.817
	(1.497)	(1.777)	(0.278)	(0.331)	(1.473)	(1.714)
Cooperative member (1=yes)	25.05*	18.62*	-1.474	-1.140	28.14**	21.15**
	(14.20)	(11.20)	(2.939)	(2.211)	(12.89)	(10.31)
Growing season rainfall (mm)	0.011	0.014	0.007***	0.007***	0.003	0.007
	(0.008)	(0.010)	(0.002)	(0.002)	(0.008)	(0.009)
Km to marketplace	0.001	-0.005	0.002	0.002	0.0004	-0.007
	(0.027)	(0.027)	(0.005)	(0.005)	(0.026)	(0.027)
Km to FRA buying point	-0.101***	-0.119***	0.009	0.011	-0.117***	-0.138***
	(0.037)	(0.044)	(0.007)	(0.008)	(0.038)	(0.045)
Observations	13,554	13,554	13,554	13,554	13,554	13,554
Number of households	6,777	6,777	6,777	6,777	6,777	6,777
Davidson-MacKinnon test of exogeneity	4.075 (Chi-sq(1) P-value =0.044)	5.769 (Chi-sq(1) P-value =0.016)	1.542 (Chi-sq(1) P-value =0.214)	1.943 (Chi-sq(1) P-value =0.163)	6.261 (Chi-sq(1) P-value =0.012)	8.724 (Chi-sq(1) P-value =0.003)

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

[18] While the exogeneity of FISP fertilizer to net off-farm income cannot be rejected, FE results (not provided) are consistent with FE-IV results.

Table 1.4 Decomposing the effects of FISP fertilizer on net farm income

	Net farm income					
	Gross value of ag. production (ZMW'1000)		Total fertilizer cost (ZMW'1000)			
	FE-IV		FE-IV		FE	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
FISP fertilizer receipt (1=yes)	-64.65**	–	-0.537	–	0.008	–
	(28.62)		(0.380)		(0.039)	
FISP fertilizer kg	–	-0.204**	–	-0.001	–	0.0003*
		(0.096)		(0.001)		(0.0002)
Year (1=2019)	19.27***	19.97***	0.037	0.040	-0.013	-0.014
	(2.526)	(2.737)	(0.044)	(0.045)	(0.040)	(0.040)
Maize price	0.353	-3.444	0.254***	0.228***	0.249***	0.254***
	(4.610)	(4.872)	(0.053)	(0.058)	(0.049)	(0.049)
Female head	-11.14***	-12.09***	-0.066	-0.065	-0.017	-0.011
	(3.751)	(4.343)	(0.066)	(0.070)	(0.054)	(0.053)
Head's education (years)	0.503	0.449	-0.001	-0.001	0.004	0.004
	(0.392)	(0.437)	(0.008)	(0.008)	(0.007)	(0.007)
Head's age (years)	0.216	0.243	-7.71e-05	8.91e-05	0.0004	0.0003
	(0.137)	(0.154)	(0.002)	(0.002)	(0.002)	(0.002)
FTAE	0.709	0.814	0.059***	0.059***	0.052***	0.051***
	(0.790)	(0.846)	(0.014)	(0.014)	(0.013)	(0.013)
Value of prod. assets (ZMW'1000)	0.004	0.004	-9.24e-05*	-9.17e-05*	-9.82e-05*	-9.82e-05*
	(0.005)	(0.005)	(5.13e-05)	(5.15e-05)	(5.21e-05)	(5.21e-05)
Landholding size (ha)	0.154**	0.187**	0.004***	0.004***	0.004***	0.004***
	(0.071)	(0.086)	(0.001)	(0.001)	(0.001)	(0.001)
Years of e-Voucher FISP	3.786**	5.140***	-0.079***	-0.070**	-0.053**	-0.055**
	(1.551)	(1.777)	(0.026)	(0.028)	(0.024)	(0.024)
Km to tarred road	-0.004	-0.014	0.0001	2.10e-05	-1.82e-05	-1.10e-05
	(0.025)	(0.026)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Cell phone ownership (1=yes)	-2.284	-0.715	0.082***	0.092***	0.079***	0.077***
	(1.477)	(1.717)	(0.024)	(0.027)	(0.022)	(0.022)
Cooperative member (1=yes)	28.42**	21.36**	0.278	0.183	0.047	0.023
	(12.88)	(10.31)	(0.171)	(0.129)	(0.033)	(0.032)
Growing season rainfall (mm)	0.003	0.006	-0.0004***	-0.0003***	-0.0004***	-0.0004***
	(0.008)	(0.009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Km to marketplace	-8.36e-05	-0.007	-0.0003	-0.0004	-0.0005	-0.0005
	(0.026)	(0.027)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Km to FRA buying point	-0.116***	-0.137***	0.0006	0.0004	0.0008	0.0009
	(0.038)	(0.045)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Constant	–	–	–	–	0.354*	0.348*
					(0.191)	(0.192)

Table 1.4 (cont'd)

	Net farm income					
	Gross value of ag. production (ZMW'1000)		Total fertilizer cost (ZMW'1000)			
	FE-IV		FE-IV		FE	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Observations	13,556	13,556	13,556	13,556	15,160	15,160
Number of households	6,778	6,778	6,778	6,778	7,934	7,934
Davidson-MacKinnon test of exogeneity	6.383 (Chi-sq(1) P-value =0.012)	8.874 (Chi-sq(1) P-value =0.003)	2.401 (Chi-sq(1) P-value =0.121)	2.289 (Chi-sq(1) P-value =0.130)	–	–

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.5 Effects of FISP fertilizer on household dietary diversity (FE-IV)

	HDDS	
VARIABLES	(1)	(2)
FISP fertilizer receipt (1=yes)	-3.843***	–
	(1.275)	
FISP fertilizer kg	–	-0.0109***
		(0.0039)
Year (1=2019)	-0.0456	0.0466
	(0.179)	(0.187)
Maize price	0.436*	0.228
	(0.238)	(0.255)
Off-farm income share	0.0841	0.201
	(0.162)	(0.147)
Female head	-0.397*	-0.417*
	(0.203)	(0.214)
Head’s education (years)	0.0078	0.0063
	(0.0233)	(0.0231)
Head’s age (years)	0.0006	0.0018
	(0.0078)	(0.0084)
FTAE	0.0651*	0.0664*
	(0.0338)	(0.0356)
Value of productive assets (ZMW’1000)	0.0002*	0.0002*
	(7.64e-05)	(8.09e-05)
Landholding size (ha)	0.0045*	0.0060**
	(0.0024)	(0.0025)
Basal fertilizer price (ZMW)	-0.451***	-0.397***
	(0.0978)	(0.0979)
Years of e-Voucher FISP	-0.0039	0.0628
	(0.0727)	(0.0740)
Km to tarred road	0.0008	4.90e-05
	(0.0017)	(0.0016)
Km to agro-dealer	-5.97e-06	0.0006
	(0.0018)	(0.0017)
Plough ownership (1=yes)	0.401**	0.581***
	(0.172)	(0.204)
Cell phone ownership (1=yes)	0.333***	0.405***
	(0.0995)	(0.103)
Cooperative/group membership (1=yes)	1.903***	1.362***
	(0.568)	(0.417)
Growing season rainfall (mm)	2.83e-05	0.0002
	(0.0003)	(0.0004)
Km to marketplace	0.0025	0.0019
	(0.0016)	(0.0016)
Km to FRA buying point	-0.0017	-0.0029
	(0.0022)	(0.0022)
Observations	13,556	13,556
Number of households	6,778	6,778
Davidson-MacKinnon test of exogeneity	14.645	13.031
	(Chi-sq(1) P-value=0.0001)	(Chi-sq(1) P-value=0.0003)

Table 1.5 (cont'd)

Notes: Robust standard errors (in parentheses) clustered at the household level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

APPENDIX B. SUPPLEMENTARY MATERIALS

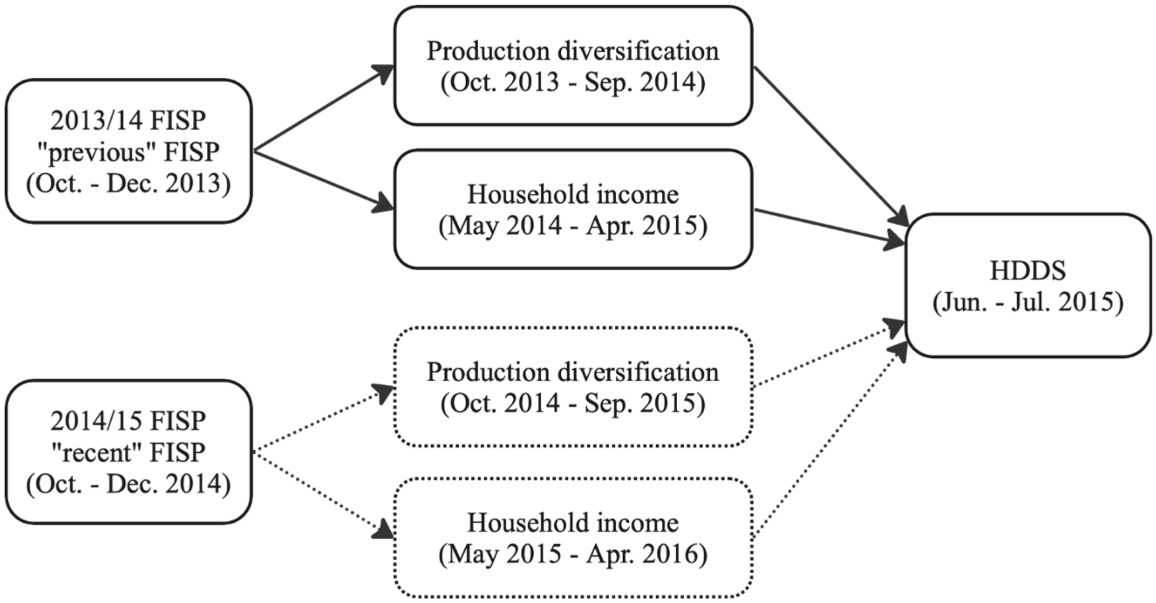
Table 1.6 P-values of the attrition bias test

Outcome variable	FISP fertilizer receipt (1=yes) specification	FISP fertilizer kg specification
SID, Herfindahl index	0.017**	0.055**
Maize share of total cropped area	0.210	0.381
Net income	0.035**	0.152
Net off-farm income	0.000***	0.006***
Net farm income	0.641	0.438
Total fertilizer cost	0.454	0.285
Total fertilizer used (kg)	0.365	0.104
Gross value of ag. production	0.805	0.624
Gross value of maize production	0.460	0.593
Gross value of non-maize production	0.842	0.499
HDDS	0.168	0.119

Notes: ***p < 0.01, **p < 0.05, *p < 0.1.

We present the p-values obtained from the regression-based test (Wooldridge, 2010) in Table 1.6. We created a regressor indicating household attrition in the second wave of the panel. Then, using only the data from the first wave, we performed IV estimation by regressing the outcome variables on the observed explanatory variables and the attrition indicator. FISP participation was instrumented by three IVs: Ruling party won parliament seat, Absolute vote spread, and their interaction. It is worth noting that due to the limited two-wave panel data, we were unable to incorporate household fixed effects into the test. While we did find evidence rejecting the null hypothesis of no attrition bias in the case of field crop SID, net income, and net off-farm income, we fail to reject this null hypothesis for the other outcome variables. Notably, we did not find any evidence of attrition bias in net farm income and the gross value of production variables, which drive the main results of the income pathway analysis. Given these results and that we do control for household FE in our analyses, we have minimal concern about attrition bias affecting the results of this study.

Figure 1.3 The association between *previous* and *recent* FISPs and the pathways



Subsidized inputs obtained in the early part of the 2014/15 agricultural year ("recent" FISP) would have influenced the production diversification in the 2014/15 agricultural year and household income during the 2015/16 marketing year, as depicted in Figure 1.3. Nonetheless, the RALS 2015 did not collect information on these periods (depicted by the dashed boxes). Furthermore, given the reference period for HDDS is June-July 2015, the recent FISP's impact on it cannot be comprehensively captured. Hence, our primary focus centers on the impact of the *previous* FISP, unless explicitly indicated otherwise.

Table 1.7 Available FISP participation data in the RALS

FISP variable	RALS 2015		RALS 2019	
	2013/14 FISP	2014/15 FISP	2017/18 FISP	2018/19 FISP
Any household member selected to receive FISP (1=yes)				✓
FISP fertilizer or maize seed receipt (1=yes)	✓	✓		✓
FISP fertilizer receipt (1=yes)	✓	✓	✓	✓
Kg of FISP top dressing fertilizer received	✓	✓	✓	✓
Kg of FISP basal dressing fertilizer received	✓	✓	✓	✓
Kg of FISP maize seed received	✓	✓		✓
Other FISP seeds receipt (1=yes)	✓		✓	

Notes: Blank indicates data are not available; ✓ indicates data are available. Information on Other FISP seeds is available only if FISP was the source for the largest transaction to acquire the seed.

Table 1.7 provides a summary of the FISP participation information available in each survey wave. The RALS 2015 and 2019 do not offer information regarding overall participation in the program (any member of the household being selected to receive FISP) for the preceding years of our interest (i.e., 2013/14 FISP and 2017/18 FISP). The only consistent information across both survey waves for the *previous* FISP is whether the household received any FISP fertilizer (row 3) and the amount of fertilizer received (rows 4 and 5). Given that fertilizer is the major input distributed via FISP, our focus centers on fertilizers. Fertilizers accounted for over 95% of total inputs distributed through the 2013/14 FISP (MAL, GRZ, 2014). For the 2017/18 agricultural year, corresponding to our second wave of the panel, no GRZ manual was produced, resulting in a lack of input allocation information for this period. Nevertheless, given that fertilizers constituted over 90% of total inputs distributed through the 2018/19 FISP (MoA, GRZ, 2018), we reasonably assume a similar predominance of fertilizer for the 2017/18 FISP.

Table 1.8 Field crop SID first-stage regression results

VARIABLES	(1) FISP fertilizer receipt	(2) FISP fertilizer kg
IV: Ruling party won parliament seat (1=yes)	0.0571**	14.739*
	(0.0237)	(8.138)
IV: Absolute vote spread (% point)	-0.0008**	-0.186
	(0.0004)	(0.142)
IV: Ruling party won × Absolute vote spread	0.0010	0.388*
	(0.0006)	(0.210)
Year (1=2019)	0.0553*	25.516**
	(0.0290)	(10.272)
Maize price (ZMW)	0.0550*	-1.457
	(0.0329)	(11.722)
Female head (1=yes)	-0.1323***	-43.50***
	(0.0368)	(12.38)
Head's education (years)	-0.0007	-0.574
	(0.0042)	(1.418)
Head's age (years)	-0.0008	-0.109
	(0.0014)	(0.462)
FTAE	0.0143**	4.643**
	(0.0060)	(2.168)
Value of productive assets (ZMW'1000)	2.82e-06	0.0025
	(4.65e-06)	(0.0024)
Landholding size (ha)	0.0011*	0.495***
	(0.0006)	(0.1495)
Basal fertilizer price (ZMW)	0.0166	10.55**
	(0.0145)	(4.604)
Years of e-Voucher FISP	-0.0116	3.316
	(0.0131)	(4.619)
Km to tarred road	0.0002	-0.0010
	(0.0003)	(0.0734)
Km to agro-dealer	0.0002	0.0947
	(0.0003)	(0.0851)
Plough ownership (1=yes)	0.0361	31.26***
	(0.0269)	(9.579)
Growing season total rainfall (mm)	3.56e-05	0.0073
	(6.14e-05)	(0.0208)
Km to marketplace	0.0001	0.0222
	(0.0003)	(0.0833)
Km to FRA buying point	-0.0001	-0.103
	(0.0003)	(0.0967)
Observations	12,930	12,930
Number of households	6,465	6,465
Kleibergen-Paap rk Wald F statistic	10.197	7.753
Hansen J statistic (overidentification test of all instruments)	4.474 (Chi-sq(2) P-value=0.107)	4.362 (Chi-sq(2) P-value=0.113)

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

The Kleibergen-Paap F statistics from the first-stage regression of the binary FISP participation is 10.197, indicating that the bias size of the IV estimator compared to the OLS estimator is less than 10 percent within a 5 percent significance level test (Stock and Yogo, 2005). This outcome leads to the rejection of the hypothesis that the instruments are weak. For the first-stage regression of the amount of FISP fertilizer received, the Kleibergen-Paap F statistics is 7.753. Although the instruments are weaker in this case, the size of the relative bias remains under 20 percent as tested at the 5 percent significance level (Stock and Yogo, 2005). The Sargan-Hansen test of overidentifying restrictions suggests that we cannot reject the null hypothesis (at the 10 percent level) that the IVs are valid in both regressions.

Table 1.9 Net income first-stage regression results

VARIABLES	(1) FISP fertilizer receipt	(2) FISP fertilizer kg
IV: Ruling party won parliament seat (1=yes)	0.0453**	14.16*
	(0.0201)	(7.298)
IV: Absolute vote spread (% point)	-0.0006*	-0.109
	(0.0004)	(0.1287)
IV: Ruling party won × Absolute vote spread	0.0007	0.2816
	(0.0005)	(0.1924)
Year (1=2019)	-0.0005	2.585
	(0.0187)	(7.141)
Maize price	0.0604**	0.759
	(0.0293)	(10.79)
Female head	-0.0741***	-28.03***
	(0.0286)	(10.60)
Head's education (years)	-0.0025	-1.055
	(0.0033)	(1.242)
Head's age (years)	0.0002	0.199
	(0.0011)	(0.441)
FTAE	0.0084*	3.242*
	(0.0049)	(1.903)
Value of productive assets (ZMW'1000)	1.24e-06	0.0010
	(4.47e-06)	(0.0018)
Landholding size (ha)	0.0006	0.3435**
	(0.0005)	(0.1404)
Years of e-Voucher FISP	0.0056	8.706**
	(0.0108)	(4.02)
Km to tarred road	0.0001	-0.0100
	(0.0002)	(0.0619)
Cell phone ownership (1=yes)	0.0091	10.50**
	(0.0145)	(4.388)
Cooperative member (1=yes)	0.4367***	104.0***
	(0.0188)	(5.546)
Growing season rainfall (mm)	-4.76e-05	0.005
	(5.05e-05)	(0.0186)
Km to marketplace	0.0003*	0.0753
	(0.0002)	(0.069)
Km to FRA buying point	-0.0002	-0.179**
	(0.0002)	(0.0883)
Observations	13,554	13,554
Number of households	6,777	6,777
Kleibergen-Paap rk Wald F statistic	8.888	6.414
Hansen J statistic (overidentification test of all instruments)	1.235 (Chi-sq(2) P-value=0.539)	0.632 (Chi-sq(2) P-value=0.729)

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.10 HDDS first-stage regression results

VARIABLES	(1) FISP fertilizer receipt	(2) FISP fertilizer kg
IV: Ruling party won parliament seat (1=yes)	0.0420**	12.38*
	(0.0201)	(7.34)
IV: Absolute vote spread (% point)	-0.0007*	-0.1374
	(0.0004)	(0.1297)
IV: Ruling party won × Absolute vote spread	0.0008	0.3576*
	(0.0005)	(0.1917)
Year (1=2019)	0.0125	12.29
	(0.0244)	(9.27)
Maize price	0.0558*	-0.736
	(0.0291)	(10.767)
Off-farm income share	-0.0771***	-16.37**
	(0.0187)	(6.68)
Female head	-0.0681**	-25.50**
	(0.0280)	(10.28)
Head’s education (years)	-0.0027	-1.043
	(0.0033)	(1.235)
Head’s age (years)	0.0001	0.1477
	(0.0011)	(0.441)
FTAE	0.0077	2.896
	(0.0048)	(1.882)
Value of productive assets (ZMW’1000)	2.12e-06	0.0015
	(4.51e-06)	(0.0016)
Landholding size (ha)	0.0006	0.3323**
	(0.0005)	(0.1348)
Basal fertilizer price (ZMW)	0.0094	8.46**
	(0.012)	(4.09)
Years of e-Voucher FISP	0.0046	7.70*
	(0.0110)	(4.13)
Km to tarred road	0.0002	-0.0171
	(0.0002)	(0.0641)
Km to agro-dealer	1.17e-05	0.0596
	(0.0003)	(0.0811)
Plough ownership (1=yes)	0.0475**	33.36***
	(0.0220)	(8.54)
Cell phone ownership (1=yes)	0.0112	10.33**
	(0.0144)	(4.34)
Cooperative member (1=yes)	0.435***	103.5***
	(0.0185)	(5.45)
Growing season rainfall (mm)	-3.26e-05	0.0073
	(0.0001)	(0.0184)
Km to marketplace	0.0003	0.0693
	(0.0002)	(0.0754)
Km to FRA buying point	-0.0003	-0.195**
	(0.0003)	(0.0904)

Table 1.10 (cont'd)

VARIABLES	(1) FISP fertilizer receipt	(2) FISP fertilizer kg
Observations	13,556	13,556
Number of households	6,778	6,778
Kleibergen-Paap rk Wald F statistic	9.220	7.113
Hansen J statistic (overidentification	0.150	0.905
test of all instruments)	(Chi-sq(2) P-value=0.928)	(Chi-sq(2) P-value=0.636)

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.11 Effects of FISP fertilizer on the Herfindahl index (FE-IV)

	Herfindahl index	
VARIABLES	(1)	(2)
FISP fertilizer receipt (1=yes)	0.223**	–
	(0.101)	
FISP fertilizer kg	–	0.0007**
		(0.0003)
Year (1=2019)	-0.0171	-0.0234
	(0.0204)	(0.0214)
Maize price (ZMW)	0.0080	0.0210
	(0.0295)	(0.0304)
Female head (1=yes)	0.0625**	0.0645**
	(0.0264)	(0.0271)
Head's education (years)	-0.0010	-0.0007
	(0.0023)	(0.0023)
Head's age (years)	-0.0002	-0.0002
	(0.0010)	(0.0011)
FTAE	-0.0186***	-0.0187***
	(0.0038)	(0.0038)
Value of productive assets (ZMW'1000)	7.80e-06***	6.65e-06**
	(2.91e-06)	(3.11e-06)
Landholding size (ha)	-0.0002	-0.0004
	(0.0003)	(0.0003)
Basal fertilizer price (ZMW)	0.0187*	0.0151
	(0.0105)	(0.0106)
Years of e-Voucher FISP implementation	-0.0125	-0.0175**
	(0.0079)	(0.0077)
Km to tarred road	4.68e-06	5.64e-05
	(0.0002)	(0.0002)
Km to agro-dealer	-1.42e-05	-4.07e-05
	(0.0002)	(0.0002)
Plough ownership (1=yes)	-0.0375***	-0.0519***
	(0.0140)	(0.0175)
Growing season rainfall (mm)	-1.32e-05	-2.51e-05
	(3.53e-05)	(3.72e-05)
Km to marketplace	-0.0002	-0.0001
	(0.0002)	(0.0002)
Km to FRA buying point	-0.0001	-8.87e-05
	(0.0002)	(0.0002)
Observations	12,930	12,930
Number of households	6,465	6,465
Davidson-MacKinnon test of exogeneity	9.529 (Chi-sq(1) P-value=0.002)	8.363 (Chi-sq(1) P-value=0.004)

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.12 Effect of FISP fertilizer on maize share of total cropped area (FE)[19]

VARIABLES	(1)	(2)
FISP fertilizer receipt (1=yes)	0.0264***	–
	(0.0097)	
FISP fertilizer kg	–	0.0001***
		(2.38e-05)
Year (1=2019)	0.0124	0.0112
	(0.0203)	(0.0203)
Maize price (ZMW)	0.0796**	0.0817**
	(0.0325)	(0.0324)
Female head (1=yes)	0.0249	0.0259
	(0.0221)	(0.0220)
Head's education (years)	0.0033	0.0033*
	(0.0020)	(0.0020)
Head's age (years)	-0.0015	-0.0015
	(0.0009)	(0.0009)
FTAE	-0.0091***	-0.0092***
	(0.0032)	(0.0032)
Value of productive assets (ZMW'1000)	5.38e-06**	5.26e-06**
	(2.12e-06)	(2.10e-06)
Landholding size (ha)	0.0002	0.0002
	(0.0003)	(0.0003)
Basal fertilizer price (ZMW)	0.0010	0.0006
	(0.0108)	(0.0107)
Years of e-Voucher FISP	-0.0149**	-0.0155**
	(0.0073)	(0.0073)
Km to tarred road	-0.0001	-0.0001
	(0.0003)	(0.0003)
Km to agro-dealer	-0.0002	-0.0002
	(0.0002)	(0.0002)
Plough ownership (1=yes)	-0.0138	-0.0154
	(0.0146)	(0.0146)
Growing season rainfall (mm)	-3.25e-05	-3.33e-05
	(3.30e-05)	(3.29e-05)
Km to marketplace	-6.05e-06	-4.32e-06
	(0.0002)	(0.0002)
Km to FRA buying point	8.08e-05	8.61e-05
	(0.0002)	(0.0002)
Constant	0.594***	0.596***
	(0.0823)	(0.0825)
Observations	14,179	14,179
Number of households	7,781	7,781

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

[19] We fail to reject the exogeneity test that FISP fertilizer can be treated as exogenous, hence report the FE regression outcomes. The FE-IV regression reveals no statistically significant effect on the maize share of the total cropped area.

Table 1.13 Effects of FISP fertilizer on total fertilizer used (kg)

	FE-IV		FE[20]	
VARIABLES	(1)	(2)	(3)	(4)
FISP fertilizer receipt (1=yes)	231.8**	–	136.7***	–
	(110.7)		(14.88)	
FISP fertilizer kg	–	0.746**	–	0.658***
		(0.298)		(0.0572)
Year (1=2019)	33.99*	31.89*	24.76	22.58
	(17.83)	(16.82)	(16.75)	(15.77)
Maize price	14.64	29.08	12.09	24.84
	(18.72)	(18.45)	(17.43)	(16.76)
Female head	-12.43	-8.616	-17.81	-9.994
	(18.77)	(17.26)	(16.22)	(14.57)
Head’s education (years)	-0.356	-0.151	0.503	0.736
	(2.597)	(2.415)	(2.477)	(2.314)
Head’s age (years)	0.0162	-0.0792	0.261	0.101
	(0.589)	(0.545)	(0.655)	(0.629)
FTAE	12.76**	12.34**	12.89**	12.00**
	(5.659)	(5.365)	(5.466)	(5.159)
Value of prod. assets (ZMW’1000)	-0.0098	-0.0102	-0.0115	-0.0116
	(0.0118)	(0.0116)	(0.0118)	(0.0117)
Landholding size (ha)	1.171**	1.048**	1.305***	1.150***
	(0.473)	(0.413)	(0.473)	(0.417)
Basal fertilizer price (ZMW)	1.352	-1.376	1.746	-1.054
	(4.424)	(4.031)	(4.283)	(3.721)
Years of e-Voucher FISP	-14.68	-18.99*	-10.26	-13.60
	(10.09)	(9.911)	(9.364)	(9.072)
Km to tarred road	-0.0746	-0.0387	-0.0811	-0.0533
	(0.0998)	(0.0888)	(0.0980)	(0.0910)
Cell phone ownership (1=yes)	21.63***	15.83**	23.24***	17.32**
	(7.869)	(7.910)	(7.308)	(7.029)
Cooperative member (1=yes)	-25.49	-1.841	16.99	9.160
	(49.37)	(33.05)	(12.45)	(12.03)
Growing season rainfall (mm)	-0.0745**	-0.0882***	-0.0723**	-0.0846***
	(0.0338)	(0.0333)	(0.0328)	(0.0315)
Km to marketplace	-0.315**	-0.293**	-0.283**	-0.287**
	(0.131)	(0.117)	(0.123)	(0.115)
Km to FRA buying point	0.271	0.350*	0.281	0.360*
	(0.193)	(0.193)	(0.191)	(0.185)
Constant			122.8**	135.4**
			(57.95)	(54.97)
Observations	13,556	13,556	15,160	15,160
Number of households	6,778	6,778	7,934	7,934
Davidson-MacKinnon test of exogeneity	0.590 (Chi-sq(1) P-value=0.442)	0.084 (Chi-sq(1) P-value=0.772)	–	–

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1. Basal fertilizer prices are included because of their potential association with the total amount of fertilizer used.

[20] We fail to reject the exogeneity of FISP fertilizer, hence report results for both the FE-IV and FE regressions.

Table 1.14 Decomposing the effect on the gross value of agricultural production

	Gross Value of Agricultural Production (ZMW'1000)					
	Gross value of maize				Gross value of non-maize	
	FE-IV		FE[21]		FE-IV	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
FISP fertilizer receipt (1=yes)	-1.056	–	0.851***	–	-55.10**	–
	(1.338)		(0.147)		(26.77)	
FISP fertilizer kg	–	-0.002	–	0.004***	–	-0.163*
		(0.004)		(0.001)		(0.086)
Year (1=2019)	0.234	0.230	0.103	0.091	17.58***	17.94***
	(0.187)	(0.186)	(0.171)	(0.167)	(2.371)	(2.484)
Maize price	1.718***	1.690***	1.706***	1.779***	-1.047	-4.216
	(0.220)	(0.234)	(0.201)	(0.200)	(4.126)	(4.386)
Female head	-0.398	-0.363	-0.246	-0.203	-10.51***	-11.09***
	(0.298)	(0.307)	(0.248)	(0.237)	(3.483)	(3.920)
Head's education (years)	-0.009	-0.008	0.006	0.007	0.409	0.378
	(0.032)	(0.031)	(0.028)	(0.028)	(0.359)	(0.390)
Head's age (years)	-0.007	-0.007	-0.003	-0.004	0.191	0.209
	(0.006)	(0.006)	(0.006)	(0.006)	(0.130)	(0.142)
FTAE	0.212***	0.208***	0.186***	0.181***	0.506	0.567
	(0.058)	(0.058)	(0.054)	(0.052)	(0.725)	(0.757)
Value of prod. assets (ZMW'1000)	-5.23e-07	-1.36e-06	-2.27e-05	-2.36e-05	0.004	0.004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.005)	(0.005)
Landholding size (ha)	0.012**	0.012**	0.011**	0.010**	0.128**	0.153**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.063)	(0.075)
Basal fertilizer price (ZMW)	-0.049	-0.048	-0.067	-0.083*	4.465**	5.044**
	(0.056)	(0.060)	(0.051)	(0.049)	(2.000)	(2.078)
Years of e-Voucher FISP	-0.350***	-0.335***	-0.282***	-0.302***	3.176**	4.219***
	(0.111)	(0.116)	(0.102)	(0.102)	(1.466)	(1.583)
Km to tarred road	0.0004	0.0003	0.0004	0.0005	-0.010	-0.018
	(0.002)	(0.001)	(0.001)	(0.001)	(0.024)	(0.025)
Cell phone ownership (1=yes)	0.103	0.110	0.086	0.055	-2.381*	-1.230
	(0.095)	(0.100)	(0.088)	(0.088)	(1.375)	(1.525)
Cooperative member (1=yes)	1.014*	0.710*	0.207	0.198	24.59**	17.38*
	(0.606)	(0.429)	(0.130)	(0.124)	(12.05)	(9.146)
Growing season rainfall (mm)	-0.002***	-0.002***	-0.002***	-0.002***	0.003	0.006
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.008)	(0.008)
Km to marketplace	-0.0007	-0.0009	-0.001	-0.001	0.005	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.025)	(0.025)
Km to FRA buying point	0.002	0.002	0.002	0.003	-0.102***	-0.119***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.032)	(0.038)

[21] We fail to reject the exogeneity of FISP fertilizer to the gross value of maize, hence report results for both the FE-IV and FE regressions. FISP fertilizer does not have a statistically significant effect on the gross value of maize production under the FE-IV regressions. Even if there is a positive effect under the FE regressions, it only marginally raises the gross value of maize production by approximately 1,025 ZMW.

Table 1.14 (cont'd)

	Gross Value of Agricultural Production (ZMW'1000)					
	Gross value of maize				Gross value of non-maize	
	FE-IV		FE		FE-IV	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Constant	–	–	1.145*	1.226*	–	–
			(0.657)	(0.661)		
Observations	13,270	13,270	15,008	15,008	13,270	13,270
Number of households	6,635	6,635	7,932	7,932	6,635	6,635
Davidson-MacKinnon test of exogeneity	2.698 (Chi-sq(1) P-value =0.101)	2.362 (Chi-sq(1) P-value =0.124)	–	–	5.543 (Chi-sq(1) P-value =0.019)	7.133 (Chi-sq(1) P-value =0.008)

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.15 Effects of FISP fertilizer on (original) net household incomes (ZMW'1000) (FE-IV)

	Net income		Net off-farm income[22]		Net farm income	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
FISP fertilizer receipt (1=yes)	-78.86*	–	4.818	–	-83.68**	–
	(44.08)		(7.133)		(39.48)	
FISP fertilizer kg	–	-0.280*	–	0.012	–	-0.292**
		(0.154)		(0.023)		(0.139)
Year (1=2019)	19.94***	21.02***	-0.639	-0.668	20.58***	21.69***
	(3.557)	(3.906)	(0.793)	(0.800)	(3.241)	(3.640)
Maize price	0.109	-5.086	-1.425	-1.201	1.534	-3.885
	(6.520)	(6.627)	(1.510)	(1.459)	(5.972)	(6.279)
Female head	-15.16***	-17.19***	-0.888	-0.908	-14.28***	-16.28***
	(5.663)	(6.614)	(1.265)	(1.314)	(5.129)	(6.118)
Head's education (years)	0.650	0.550	0.161	0.161	0.489	0.388
	(0.517)	(0.596)	(0.102)	(0.104)	(0.483)	(0.566)
Head's age (years)	0.276	0.315	0.007	0.005	0.269	0.310
	(0.212)	(0.239)	(0.051)	(0.051)	(0.177)	(0.208)
FTAE	0.075	0.306	0.341	0.344	-0.266	-0.037
	(1.399)	(1.451)	(0.268)	(0.269)	(1.252)	(1.317)
Value of productive assets (ZMW'1000)	0.035	0.035	-0.003	-0.003	0.039	0.039
	(0.053)	(0.053)	(0.011)	(0.011)	(0.042)	(0.042)
Landholding size (ha)	0.409	0.461*	0.054	0.052	0.355*	0.408*
	(0.255)	(0.279)	(0.046)	(0.048)	(0.212)	(0.234)
Years of e-Voucher FISP	5.245**	7.052***	0.215	0.131	5.030**	6.922***
	(2.349)	(2.724)	(0.447)	(0.511)	(2.109)	(2.433)
Km to tarred road	-0.003	-0.016	-0.003	-0.002	0.0003	-0.014
	(0.031)	(0.034)	(0.005)	(0.005)	(0.030)	(0.032)
Cell phone ownership (1=yes)	-2.286	-0.045	1.098***	1.015***	-3.384*	-1.060
	(1.864)	(2.411)	(0.307)	(0.358)	(1.801)	(2.274)
Cooperative member (1=yes)	35.80*	30.52*	-1.870	-0.994	37.67**	31.51**
	(19.99)	(16.50)	(3.204)	(2.504)	(17.92)	(14.89)
Growing season rainfall (mm)	0.020*	0.025*	0.009***	0.009***	0.011	0.017
	(0.012)	(0.014)	(0.002)	(0.002)	(0.011)	(0.012)
Km to marketplace	0.008	0.002	0.001	0.002	0.007	-0.0004
	(0.037)	(0.039)	(0.006)	(0.006)	(0.035)	(0.037)
Km to FRA buying point	-0.147***	-0.178***	0.010	0.011	-0.157***	-0.189***
	(0.050)	(0.063)	(0.009)	(0.010)	(0.050)	(0.062)
Observations	13,554	13,554	13,554	13,554	13,554	13,554
Number of households	6,777	6,777	6,777	6,777	6,777	6,777
Davidson-MacKinnon test of exogeneity	2.972 (Chi-sq(1) P-value =0.085)	4.633 (Chi-sq(1) P-value =0.031)	1.631 (Chi-sq(1) P-value =0.202)	1.087 (Chi-sq(1) P-value =0.297)	4.347 (Chi-sq(1) P-value =0.037)	6.444 (Chi-sq(1) P-value =0.011)

Notes: Robust standard errors (in parentheses) clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

[22] While the exogeneity of FISP fertilizer to net off-farm income cannot be rejected, FE results (not provided) are consistent with FE-IV results.

APPENDIX C. THEORETICAL FRAMEWORK

Our theoretical framework is based on an agricultural household model (Sadoulet and Janvry, 1995; Singh, Squire, and Strauss, 1986). In many developing countries, a significant portion of the population relies on agriculture for their livelihoods, engaging in both the production and consumption of agricultural products. These agricultural households produce both for sale and own consumption, utilizing agricultural inputs that are procured and self-sourced. In contexts with absent or imperfect markets, production and consumption decisions are interlinked (i.e., "non-separable"). Production decisions are affected by household characteristics and preferences, and they are not solely made based on profit maximization constrained by production functions. We adopt a non-separable perspective to analyze the decisions of Zambian smallholder households, building upon the adaptations of agricultural household models used by Van Dusen and Taylor (2005) and Smale, Moursi, and Birol (2015).[23]

Households maximize their utility by determining which agricultural products ($j = 1,2, \dots, J$) to produce, along with their aggregate production output $\boldsymbol{Q} = (Q_1, \dots, Q_J)$. They also decide on consuming on-farm produced agricultural products $\boldsymbol{X} = (X_1, \dots, X_J)$ and other market-purchased goods Z, while accounting for their demographic and socioeconomic characteristics ($\mathbf{V}^H$). The prices of on-farm produced agricultural products are represented by a price vector $\boldsymbol{p} = (p_1, \dots, p_J)$, while the price of all other market-purchased goods is normalized to 1. The

[23] We recognize that production and consumption decisions are not simultaneously determined. Input allocation choices are made based on risk preferences and price expectations, while consumption choices rely on realized income and prices. While studies such as Dillon, McGee, and Oseni (2015), Saha (1994), Singh, Squire, and Strauss (1986), and Vijayalaxmi, Umesh, and Saravanakumar (2020) delve into discussions about dynamic non-separable household models, where production decisions precede consumption decisions, and factors like risk and uncertainty are accounted for, we opt for a simplified static model as in Smale, Moursi, and Birol (2015). We posit that households' risk preferences exhibit little change over time, and hence can be addressed by the inclusion of household fixed effects.

household's optimization decision is subject to (i) a full income constraint and (ii) market-related constraints:

$$\begin{aligned}&\max_{\boldsymbol{X},Z,\boldsymbol{Q}} U(\boldsymbol{X}, Z; \mathbf{V}^{\boldsymbol{H}})\\ &\quad subject\ to \quad (i) \quad Z = \bar{Y} + wT + \boldsymbol{p}(\boldsymbol{Q} - \boldsymbol{X}) - C(\boldsymbol{Q}; FISP, \mathbf{V}^{\boldsymbol{F}})\\ &\qquad\qquad\qquad (ii) \ \ M(\boldsymbol{Q}, \boldsymbol{X}; \mathbf{V}^{\boldsymbol{M}}) = 0.\end{aligned}$$

The full income constraint stipulates that consumption expenditure on market-purchased goods must not exceed the household's income. Household income consists of exogenous income ($\bar{Y}$), the household's time endowment (T) valued at the local market wage (w), and farm profit after accounting for own consumption and costs, $C(\boldsymbol{Q}; FISP, \mathbf{V}^{\boldsymbol{F}})$, in which the households' technological constraint is embedded. The cost function is affected by farm-specific characteristics ($\mathbf{V}^{\boldsymbol{F}}$), including input prices. The focal policy context, participation in the FISP, also directly influences the cost function by reducing the cost and enhancing the accessibility of agricultural inputs.[24] Household production and consumption decisions are also shaped by the market environment or market characteristics ($\mathbf{V}^{\boldsymbol{M}}$) that affect the market-related constraints.[25] Factors such as high transaction costs or missing markets may disrupt households' marketing of their agricultural products or purchasing of commodities, necessitating them to meet their consumption needs through their own production. In such cases, for example, the market-related constraint $M(\cdot)$ would take a form such as $X_j - Q_j = 0$ for product j (Van Dusen and Taylor, 2005).

The decision rules for optimal levels of production $\boldsymbol{Q}$ and consumption $(\boldsymbol{X}, Z)$ are represented as follows:

$$\boldsymbol{Q} = \boldsymbol{Q}(\boldsymbol{p}, \mathbf{V}^{\boldsymbol{H}}, \mathbf{V}^{\boldsymbol{F}}, FISP, \mathbf{V}^{\boldsymbol{M}}) \tag{1.1}$$

[24] Participation in FISP is a decision undertaken by households. While we incorporate FISP as part of exogenous characteristics within the theoretical framework, we address their selection into FISP empirically in section 1.4.
[25] In the empirical model, we include all household, farm, and market characteristics, as well as prices, as control variables $\mathbf{V}$ without categorization.

$$\begin{aligned} \boldsymbol{X} &= \boldsymbol{X}(\boldsymbol{p}, Y, \mathbf{V}^{\boldsymbol{H}}, \mathbf{V}^{\boldsymbol{F}}, FISP, \mathbf{V}^{\boldsymbol{M}}) \\ Z &= Z(\boldsymbol{p}, Y, \mathbf{V}^{\boldsymbol{H}}, \mathbf{V}^{\boldsymbol{F}}, FISP, \mathbf{V}^{\boldsymbol{M}}), \end{aligned} \tag{1.2}$$

where Y represents the full income corresponding to the optimal production level $\boldsymbol{Q}$, hence depending on prices, household, farm, and market characteristics, and participation in FISP. Preferences for dietary diversity are integrated within the utility function $U(\cdot)$, and the household's dietary diversity outcome D is contingent upon their optimal choices in production and consumption, as captured in the subsequent reduced form relationship:

$$D = D(\boldsymbol{p}, Y, \mathbf{V}^{\boldsymbol{H}}, \mathbf{V}^{\boldsymbol{F}}, FISP, \mathbf{V}^{\boldsymbol{M}}). \tag{1.3}$$

HDDS is thus affected by various factors, including prices, full income, as well as household, farm, and market characteristics, along with participation in the FISP.

CHAPTER 2:

MARKET CHANNEL AND HETEROGENEOUS STORAGE BEHAVIOR IN REPONSE TO MULTIPLE RISKS: THE CASE OF NIGERIAN MAIZE TRADERS

2.1 Introduction

The agrifood systems and value chains of developing countries have experienced significant growth and transformation over the past few decades, primarily driven by trade liberalization, privatization of agricultural parastatals, urbanization, and income growth (Muyanga et al., 2019; Reardon, 2015; Reardon, Liverpool-Tasie, and Minten, 2021). While such changes have occurred across all segments of the value chains, the middle segment or the midstream, which includes logistics, processing, and wholesaling, has received significantly less research and policy attention than the upstream and downstream segments (Reardon, 2015). Yet, these midstream actors are vital because they serve as crucial intermediaries between producers and consumers within the agrifood value chains (Abate et al., 2015; Reardon, 2012).

The significance of midstream actors in staple food value chains becomes particularly pronounced in economies heavily reliant on staple foods, as observed in numerous developing countries. Specifically, maize stands out as a principal staple crop and a primary focus of agricultural and food policies throughout Sub-Saharan Arica (Cairns et al., 2013; FAO, 2018). In Nigeria, for example, where over 70% of households are engaged in crop farming, maize is the most widely cultivated crop (National Bureau of Statistics, 2019), serving both as a staple food and an important ingredient for animal feed (Herrero et al., 2014; USDA, 2019). Among the midstream actors in the maize value chain, maize wholesale traders act as the “funnel” through which maize is sold to the market. They directly influence the safety, quality, and price of maize through activities like storage, spoilage management, and transportation.

As agrifood value chains expand and lengthen (e.g., in terms of geographical distance or number of actors), they become increasingly susceptible to a range of risks that are prevalent throughout these value chains and can impact the entire system. In this study, we focus on Nigerian maize wholesale traders as representative midstream actors and analyze their storage behaviors in response to weather risks, as well as their past experiences with weather, conflict, and spoilage shocks. We first examine how these risks shape the decision to store maize and then specific damage control practices (i.e., applying chemicals or using non-chemical methods) among traders who opt for storage. Furthermore, we explore how these storage behaviors vary based on traders' primary market channel choices, specifically between selling to "modern" buyers such as industrial food and feed mills and "traditional" buyers like consumers, other wholesalers, and retailers. Modern buyers are more likely to demand maize that meets specific quality standards, such as being free from contamination or having lower levels of chemical residues, and often have contracts or arrangements settled upfront to ensure a steady supply of such maize. Hence, traders with different market channels may be driven by distinct incentives, resulting in varying responses to risks.

Considerable research attention has been directed towards examining traders in developing countries. With the shift towards market liberalization and governments disengaging or scaling down their involvement in agricultural marketing, private traders started to participate in the market. Consequently, the degree of competition among them has been of great interest (Dillon and Dambro, 2017). While a large number of traders capitalized on reduced transaction costs and entered the market openly, some still encountered barriers and risks during market entry. In addition, the presence of numerous traders in certain markets did not necessarily indicate competitiveness (Barrett, 1997; Dillon and Dambro, 2017; Staatz, Dioné, and Dembele, 1989). Some research focused on spatial price differentials and market integration to assess traders' competitiveness (Barrett, 1996; Dercon, 1995; Ravallion, 1986). Others focused on the costs and margins associated with traders' activities (Dessalegn, Jayne, and Shaffer, 1998; Fafchamps, Gabre-Madhin, and Minten, 2005; Gabre-Madhin, 2001). A prominent risk identified as hindering traders from entering the market or altering their profit was mainly attributed to 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 these costs, leading to price dispersion across markets.

More recent studies have examined the impacts of climate change perceptions on traders' trading activities and livelihoods (Arku, Angmor, and Adjei, 2017) and the effects of weather risks on their technology adoption behavior (Liverpool-Tasie and Parkhi, 2021). [26] [27] Few studies, however, have investigated the impact of spoilage or conflict risks on traders. Grain traders bear the risk of spoilage that may occur between the purchase and sale of grain (Dillon and Dambro, 2017), and their activities can also be adversely affected by prevalent conflicts, which disrupt the production system, transportation, and/or the markets. Hastings et al. (2022) is an exception that explored the role of conflicts in price transmission and market integration; however, it did not examine the impact on traders' *behavior*.[28] The impacts of multiple risks stemming from climate change, spoilage, and conflicts on traders, particularly in terms of their behavior, have not been unexplored. Our study aims to help bridge this gap by focusing on traders' storage behaviors.

Grain storage plays an important role in smoothing availability (and consumption) and

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[26] 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.

[27] 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 crop production (Belay et al., 2017; Di Falco, Veronesi, and Yesuf, 2011; Holden and Quiggin, 2017).

[28] For a review of conflicts in the international trade literature, see, for example, Reuveny (2000).

stabilizing prices (Myers, 2013). As the private sector trading has expanded, considerable research has centered on evaluating the efficiency of private sector storage and its effect on commodity prices and production (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 demand elasticity (Brennan, 2003; Knudsen and Nash, 1990). In a more recent context, Liverpool-Tasie and Parkhi (2021) recognized climate-induced risk as a factor influencing traders' decisions regarding storage and the mitigation of damages (e.g., mold growth) to stored maize. Building on Liverpool-Tasie and Parkhi (2021), our study focuses on multiple risks, rather than price arbitrage, as key determinants in traders' storage behavior.

One important aspect that has been neglected in analyzing traders' behavior, including their decisions to store and control damages to stored products, is the consideration of their specific target market. While the selection of market channels has been extensively discussed in the literature on farmers' decision-making, a significant gap exists in understanding how these considerations apply to traders. The literature on farmers includes studies on the factors affecting their choice of market channels (Arinloye et al., 2015; Mabuza, Ortmann, and Wale, 2014; Negi et al., 2018; Xaba and Masuku, 2013), as well as its impact 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 the best of our knowledge, this paper is the first to examine the effects of weather, spoilage, and conflict risks on wholesale traders in agrifood value chains, specifically focusing on their storage behaviors in relation to their primary market channel choices. We consider storing maize as one of the value-adding technologies that traders can adopt and that is susceptible to these risks (Liverpool-Tasie and Parkhi, 2021). Using data from a large sample survey of Nigerian maize traders, we apply a triple hurdle model (Burke, Myers, and Jayne, 2015) to explore the effects of multiple risks on maize traders' decisions, including: (i) the selection of their main market channel; (ii) the adoption of maize storage conditional on their market channel; and (iii) the employment of damage control practices to prevent spoilage conditional on their market channel and storing of maize.

This paper contributes to the literature in three ways. First, we contribute to the currently thin understanding of the behavior of midstream actors within agrifood value chains in developing countries. We help to fill this gap by investigating the storage behaviors of Nigerian maize traders in response to multiple risks, broadening the analysis beyond the weather risks explored by Liverpool-Tasie and Parkhi (2021) to incorporate the impact of past weather, spoilage, and conflict shocks. Second, we add to the literature on market channel choice, an area that has traditionally focused on farmers. By extending this discussion to explore maize traders' choices between different market channels, we reveal that market channels are linked to the impact of risks on traders' storage behaviors. Comprehending how risks affect different trader groups, distinguished by market channels, has the potential to inform tailored policy measures that effectively address the risks. And third, we extend the triple-hurdle model of Burke, Myers, and Jayne (2015) to analyze traders' storage adoption across different market channels. While triple-hurdle models have been used within the technology adoption literature (Claytor, 2015; Duniya, 2018; Jensen et al., 2015), we introduce an initial stage involving traders' selection of a primary market channel between traditional and modern. We recognize that traders selling through each market channel both adopt storage but possibly differently (Singbo et al., 2021). Additionally, we employ a bivariate probit model in the third stage for the selection of two distinct damage control practices: the application of chemical and/or non-chemical methods for stored maize.

2.2 Conceptual Framework

Our conceptual framework and theoretical model largely draw from the work of Liverpool-Tasie and Parkhi (2021), with our contributions focusing primarily on incorporating the impact of past shock experiences and the heterogeneous effects by market channels. 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 the maize and/or applying damage control practices during storage), and selling it. While we assume maize traders are price takers, it is known that maize with certain qualities, such as meeting some food safety standards required by buyers or having minimal 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; Sanou et al., 2021).[29] 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 manage the quality of maize.

However, traders' activities, including buying, storing, and selling maize, entail risks and costs. Weather 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 increase the likelihood

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

of pest and disease incidence in stored maize, subsequently affecting the effectiveness of damage control practices, as well as the expected quantity, quality, and price of maize that traders can sell to buyers (Liverpool-Tasie et al., 2019; Liverpool-Tasie and Parkhi, 2021; Stathers, Lamboll, and Mvumi, 2013; Suleiman, Rosentrater, and Bern, 2013; Tefera, 2012).

Moreover, the impact of extreme weather variations on traders' storage decisions may vary based on their primary market channels. Traders selling to modern market channels are more likely to have established supply contracts or agreements with buyers that mandate a stable and reliable supply of high-quality maize.[30] Therefore, they might be more inclined to store maize during extreme weather variations, as doing so could help them compensate for potential losses from these risks and ensure a consistent supply of maize. Additionally, the anticipation of premium prices during supply shortages resulting from extreme weather conditions might incentivize traders to store maize and release it strategically. On the other hand, traders selling to traditional market channels may approach storage differently. Given that storing maize under extreme weather conditions carries higher risks, they might prioritize immediate sales for buyers in demand.

Traders' past experiences of weather and conflict shocks, such as disruptions in sourcing maize due to floods, droughts, or conflicts involving Boko Haram and farmer-herder clashes, can also affect their current storage behavior. Traders who faced such disruptions in the past may tend to store maize as they become more cautious in their efforts to ensure a stable supply. Conversely, it is also plausible that traders opt not to store simply because they were unable to

[30] Indeed, our data reveal that around 77% of traders who sell to feed mills and 73% of traders who sell to flour mills, the main buyers in the modern market channel, engage in regular contractual agreements or pre-arranged arrangements with their clients (with usual contract beforehand). On the other hand, for those selling to the traditional channel, such as retailers, customers, and other rural traders, about 50% rely on spot transactions where clients visit the market and purchase maize as needed.

source sufficient maize to store after selling to buyers. Hence, traders' storage responses to these shocks remain empirical questions, whether they are selling to modern or traditional market channels.

Prior exposure to spoilage shocks, like aflatoxin outbreaks or infestations of pests and rodents affecting stored maize, is also an important factor that can alter traders' storage behavior, particularly affecting their decision to apply damage control practices, which can directly help in preventing the recurrence of such spoilage shocks. We conjecture that traders, regardless of their market channels, are likely to employ damage control practices if they have faced spoilage shocks in the past and have a heightened perception of spoilage risk. However, while both chemical and non-chemical methods can help prevent damage to stored maize, there are food safety concerns linked to the application of chemicals, as chemical residues in maize have the potential to pose significant health risks (Kadjo et al., 2020). Consequently, traders primarily engaged in the modern market channel may be less inclined to use chemicals, opting instead for non-chemical methods, to ensure minimal chemical residues in maize. In contrast, those selling primarily through the traditional market channel might be more open to using both methods. A similar conjecture regarding damage control practices applies in response to weather risks as well as traders' past experiences with weather and conflict shocks.

Theoretical Model

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 (iii) costs of buying maize and costs associated with storing and/or applying chemicals or using non-chemical methods 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 weather, spoilage, and conflict 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 becoming damaged is likely to escalate with prolonged storage periods. The market sales price of maize is expressed as $p_s^t(h,t)$, where h denotes maize quality and t indicates the t^{th} period subsequent to the purchase of maize (with $t = 0$ indicating the time of purchase). The amount of maize 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 $\boldsymbol{y}$ to prevent spoilage from insect or rodent infestation and/or mold growth. There are two types of storage practices, denoted as $\boldsymbol{y} = (y^1, y^2)$, where y^1 represents the application of chemicals such as fumigants, pesticides, and repellents, while y^2 represents the use of non-chemical methods such as application of pepper, ash, or traditional medicine, or the use of hermitic bags.[31] Both methods can be effective in preventing damage to stored maize. We denote the prices for using chemical and non-chemical methods as a vector, $\boldsymbol{p_y}$.

The damage control function, D, represents the share of stored maize that remains undamaged due to the application of damage control practices (Lichtenberg and Zilberman, 1986). The damage control function is expressed as $D(\boldsymbol{y},t)$, which increases with $\boldsymbol{y}$, decreases with t, and ranges between 0 and 1. The quantity of maize that a trader can sell in period t, $Q_s^t\big(Q_z, D(\boldsymbol{y},t)\big)$, depends on the amount of stored maize as well as the damage control function and is non-decreasing in D. The quality of maize also depends on it, denoted as $h(D(\boldsymbol{y},t))$. In

[31] While the use of hermetic bags represents a fundamentally different type of technology compared to the application of ash, pepper, or traditional medicine, we could not separate it out due to the small number of observations and therefore categorize it as a non-chemical method.

addition, we assume that traders determine whether to store maize or sell it immediately upon purchase. We further simplify this assumption by considering that if they decide to store, they store all of the purchased maize, and subsequently, 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 represented by a vector $\boldsymbol{k}$ that consists of current weather risks and past experiences of shocks. As previously discussed, such events could disrupt traders' ability to secure and store maize, as well as manage damage to stored maize, which, in turn, affect the quality and price of maize available for sale.

We further assume that maize traders encounter varying effective sales prices depending on their market channels. Traders selling to the modern channel may receive higher prices for maize that meets certain quality standards. Additional costs, such as drying maize or testing maize quality, are assumed to be incorporated into the effective price. Even if the modern market does not offer price premiums, traders selling to the modern channel may encounter more stable demand and market prices compared to those selling to the traditional channel. This is because the modern channel often operates based on contracts or pre-arrangements. Consequently, the effective price of selling to market channel j is expressed as $p_s^t(h, t, \boldsymbol{k}; j)$. Additionally, traders possess distinct underlying characteristics, represented by exogenous variables $\boldsymbol{v}$, which would primarily affect the efficacy of managing damage, $D(\boldsymbol{y}, t, \boldsymbol{k}; \boldsymbol{v})$. Thus, traders' expectations on the market price for selling to each channel at time t can be represented as:

$$E(p_s^t; j) = E\left[p_s^t\left(h\left(D(\boldsymbol{y}, t, \boldsymbol{k}; \boldsymbol{v})\right), t, \boldsymbol{k}, p_s^0; j\right)\right], \tag{2.1}$$

which is also contingent on the current market price. Subsequently, the expected profit from selling maize to market channel j is:

$$E\left(\pi^j\right) = p_s^0(h; j) * (Q_b - Q_z)$$

$$+ E\left[p_s^t\left(h\left(D(\boldsymbol{y}, t, \boldsymbol{k}; \boldsymbol{v})\right), t, \boldsymbol{k}, p_s^0; j\right)\right] * E\left[Q_s^t\left(Q_z, D(\boldsymbol{y}, t, \boldsymbol{k}; \boldsymbol{v})\right)\right]$$

$$- (p_b * Q_b + p_z * Q_z * t + \boldsymbol{p_y} * \boldsymbol{y} * Q_z). \tag{2.2}$$

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

The expected profit maximization problem provides the following set of decision rules for determining the demand for storage and the adoption storage practices, conditional on storing at time t:

$$Q_z^j(t) = z^j(E(p_s^t), p_s^0, \boldsymbol{p_y}, p_z, p_b, E(\boldsymbol{k}), \boldsymbol{v}) \tag{2.3}$$

$$\boldsymbol{y}^j(t) = \boldsymbol{y}^j(E(p_s^t), p_s^0, \boldsymbol{p_y}, p_z, p_b, E(\boldsymbol{k}), \boldsymbol{v}) \text{ when } Q_z^j(t) > 0 \tag{2.4}$$

Our conceptual framework suggests that current weather risks would deter the adoption of storage among traders selling to the traditional channel, whereas encouraging those in the modern channel. Once traders decide to store maize, we anticipate that both groups would adopt damage control practices under adverse weather conditions, albeit with different focuses: traders selling to the modern channel would lean towards non-chemical methods, while those in the traditional channel would use both chemical and non-chemical methods. The effects of past shock experiences on storage adoption needs empirical testing, but traders' incentives for adopting damage control practices are likely to mirror those concerning weather risks.

2.3 Data

We use data from a survey of maize wholesale traders conducted in late 2021, serving as the second panel following an initial survey in 2017. The 2017 survey covered the major maize markets in Nigeria, including Kano, Kaduna, Katsina, and Plateau states in northern Nigeria, which are the primary maize producing areas, and Oyo state in southern Nigeria, a major maize consuming region where some production also takes place. In each state, the city with the primary maize market was selected, and all maize markets within that city were listed.[32] Across these city markets in the five study states, all traders, except those who were unreachable, were interviewed.

In addition to city markets, traders in regional markets were also interviewed. For each northern study state, all regional markets serving other states in Nigeria or other countries were listed, and the top five markets with the highest total maize volume were selected.[33] Traders within each selected regional market were categorized into two groups: the ‘large trader stratum’, comprising those with maize sales over 32 tons during a typical month in the high maize trading season (from August to February), and the ‘small trader stratum’, consisting of those with maize sales below 32 tons during the same period.[34] To ensure diverse representation across different scales of operation, 30 traders were randomly selected based on the proportion of small and large traders within each regional market.[35]

From the traders interviewed in the 2017 survey, a total of 1,109 traders, including 584 traders from Kano, 136 from Kaduna, 170 from Katsina, 137 from Plateau, and 80 from Oyo, were reinterviewed in 2021, forming the sample for our study.[36] The survey collected comprehensive information, including maize traders’ demographic characteristics, assets, maize purchases and sales, value adding, experience of business environment shocks, and their responses to the shocks. Trading activities, including the purchases and sales of maize, were

[32] The main cities selected were Kano City in Kano; Katsina in Katsina; Kaduna in Kaduna; Jos in Plateau; and Ibadan in Oyo.
[33] Selected regional markets include Bichi, Wudil, Darki, Rimin Gado, and Danbatta in Kano state; Dandume, Bakori, Sheme, Mashi, and Batsari in Katsina state; Pambegwa, Giwa, Makarfi, Saminaka, and Birnin Gwari in Kaduna state; and Mangu, Panyam, Jengre, Kombun, and Bokkos in Plateau state.
[34] The cutoff of 32 tons represents the average quantity of maize traded during the peak sales period across all the regional markets in the study states.
[35] The share of small traders within selected regional markets is approximately 69% in Kano, 44% in Katsina, 31% in Kaduna, and 57% in Plateau.
[36] Two traders’ location information (including the state in which they operate) is missing. The 1,109 traders represent 93% of the sample interviewed in the 2017 survey, with 7% having exited the maize trading business.

surveyed for the high trading season (August 2020-February 2021), low trading season (March 2021-July 2021), and the last transaction (the most recent batch sold before the survey). In addition, we obtained rainfall and temperature data at the local government level from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) and Climate Data Store (CDS), respectively, and linked them to traders' locations.

Table 2.1 displays the variables used in the analysis, along with their summary statistics. The dependent variables include traders' storage behaviors and their market channels. Information on storage behaviors was exclusively collected for the last transaction. Among the traders in the survey, 64% stored maize purchased in their most recent transaction. Within this subgroup, 20% applied chemicals, and 5% used non-chemical methods to protect the stored maize from damage.

Traders engage in the sales of maize across various market channels, including consumers, other wholesalers, retailers, processors, and other entities. Processors primarily consist of industrial feed mills and flour mills (or the food industry), while the other entities include governmental and non-governmental organizations, albeit representing a minority share.[37] We have categorized these five market channels into two main channels: modern and traditional. The modern market channel encompasses processors and the other entities, which have emerged more recently as formal market channels. In contrast, the traditional market channel encompasses consumers, other wholesalers, and retailers. Given that traders typically sell to multiple market channels, we determined their main channel based on the percentage of maize sold to each of these five channels during the high trading season. We then constructed a

[37] There are only 7 traders in total who mainly sold to other entities.

binary market channel variable (modern vs. traditional) based on this determination.[38]

The risks that traders face in the maize market consist of current weather risks and past experience of extreme weather events, spoilage, and violent conflicts. Rainfall and temperature variability, represented by the coefficient of variations (CV) of monthly values, were included as indicators of current weather risks and serve as a proxy for expected weather variability during storage. These values were computed using monthly rainfall and temperature data within traders' business area during the growing season, April-July 2021, a period that directly affects maize supply (Liverpool-Tasie and Parkhi, 2021) and also closely precedes the time when the majority of traders stored maize, if they engaged in storage.

The experience of weather shocks was derived from traders' responses to encountering any of the following problems over the previous year, from August 2020 to July 2021: maize shortage due to production disruptions caused by floods or droughts; significant delays in receiving maize due to road washouts; and washouts or floods in the market destination area. The experience of spoilage shocks was constructed based on traders' responses to encountering any of the following issues during the same period: aflatoxin outbreaks; infestations of pests or rodents affecting stored maize; and severe spoilage of maize, such as mold contamination. Finally, the experience of conflict shocks was determined by traders' responses to encountering any of the following challenges during the same period: Boko Haram conflicts in the North directly affecting their ability to sell maize; Boko Haram conflicts in the North directly affecting their ability to buy maize from farmers or other traders; farmer-herder conflicts affecting their ability to buy maize from farmers; and other insecurity problems such as banditry or kidnapping

[38] In cases where there was an equal percentage of maize sold to each channel, preventing the determination of the main buyer, we proceeded to examine the percentage of maize sold to each channel during the low trading season. If a tie still existed during the low season, we further considered the traders' last transaction. The main market channel could not be determined for 52 (of 1,109) traders, as they had multiple main buyers, even in their last transaction.

impacting their ability to trade maize.

Summary statistics for the explanatory variables indicate that 88% of the traders are male, and 71% have completed formal education, which includes primary, secondary, or post-secondary education. On average, traders possess approximately 20 years of trading experience. Only a small fraction of traders received training on maize storage techniques, either from government or non-government sources, between August 2020 and July 2021, or government training upon entering the trading business. A quarter of traders operate on a large scale, with monthly sales exceeding 32 tons during the peak season, and more than half of the traders are members of trader associations. These associations include general wholesaler associations, which are not limited to maize, and maize trader associations, both operating within the traders' market.[39] Moreover, 14% of traders are involved in other income-generating activities. The distance to the highway, 5km on average, serves as a proxy for traders' market accessibility, and the maize sales price serves as a proxy for traders' expected market price.

2.4 Empirical Model and Estimation

Market participation or technology adoption has been conceptualized as a two-stage process involving the decision of (i) whether to participate in the market (or adopt the technology) in the first stage, and (ii) the intensity of participation (or adoption) in the second stage (Bellemare and Barrett, 2006; Goetz, 1992). However, more recently, Burke, Myers, and Jayne (2015) introduced a three-stage approach known as the triple-hurdle model to account for potential heterogeneity in the population of interest. In our study, a double-hurdle approach for the adoption of storage would have been appropriate if all maize traders in the sample primarily sold

[39] Traders frequently held memberships in multiple types of trader associations. Among these, 19% were exclusively involved in associations encompassing all types of wholesalers within the market (not limited to maize), while 76% participated solely in associations for maize wholesale traders within the market. Less than 1% of traders had an exclusive membership in a trader association at the state or national level.

to the same type of market channel, either the modern or traditional channel. However, given that maize traders sell to different market channels, their storage behaviors and the relationships between multiple risks and these behaviors may vary among traders selling to different market channels. Hence, we employ a triple-hurdle approach, extending the double-hurdle approach taken by Liverpool-Tasie and Parkhi (2021) in their assessment of the adoption of storage techniques.

Figure 2.1 illustrates the triple-hurdle approach employed in this paper. In the first stage, traders determine whether to primarily sell to the modern or traditional market channel, and we apply a probit model to represent this decision. Selecting a market channel is akin to choosing whether to participate in a specific market segment, similar to the first stages of the double-hurdle approaches used in market participation. In the second stage, traders selling to each market channel decide whether to store maize or not, represented by a probit model. In line with the approach of Liverpool-Tasie and Parkhi (2021), we consider the adoption of damage control practices conditioned on the decision to store. Consequently, in the third stage, we examine the damage control practices used by traders who sell to the traditional channel and store versus those who sell to the modern channel and store. Traders selling to the traditional channel decide whether to apply chemical and/or non-chemical methods, conditional on storage. As traders can apply both types at the same time, we employ a bivariate probit model to simultaneously estimate the likelihood of applying these treatments (Crick et al., 2018). On the other hand, for traders primarily selling to the modern channel, we utilize a probit model to determine whether they opt for any damage control practices (either chemical or non-chemical methods) or not, due to the limited number of observations.[40]

[40] Standard errors could not be estimated under the bivariate probit model due to the limited number of observations of traders selling to the modern channel and storing. While the third-stage analysis for traders selling to the

The triple-hurdle framework used in this paper diverges from the approach taken by Burke, Myers, and Jayne (2015) in that we consider traders selecting their primary market channel in the first stage, and both traders primarily selling to the modern and traditional channels adopt storage and damage control practices, albeit potentially in different ways. We consequently assume a sequential relationship between market channel decisions and storage decisions.[41] The full triple-hurdle specification is presented as follows:

$$m_i = \beta_0 + \boldsymbol{v}_i\boldsymbol{\beta}_1 + \beta_2 p_i + \boldsymbol{k}_i\boldsymbol{\beta}_3 + \boldsymbol{state}_i\boldsymbol{\beta}_4 + \varepsilon_i \quad (2.5)$$

$$z_i^j = \gamma_0^j + \boldsymbol{v}_i\boldsymbol{\gamma}_1^j + \gamma_2^j p_i + \boldsymbol{k}_i\boldsymbol{\gamma}_3^j + \boldsymbol{state}_i\boldsymbol{\gamma}_4^j + \epsilon_i^j \quad (2.6)$$

$$y_i^{n,j} = \theta_0^{n,j} + \boldsymbol{v}_i\boldsymbol{\theta}_1^{n,j} + \theta_2^{n,j} p_i + \boldsymbol{k}_i\boldsymbol{\theta}_3^{n,j} + \boldsymbol{state}_i\boldsymbol{\theta}_4^{n,j} + \xi_i^{n,j} \text{ for } n = 1,2, \quad (2.7)$$

where m represents the binary main market channel variable, indicating whether trader i primarily sells to the modern channel ($m = 1$) or traditional channel ($m = 0$). In the second stage, z^j is a binary variable indicating whether a trader stores maize or not, conditional on selling to market channel j = 1 (modern) or 2 (traditional). In the third stage, $y_i^{n,j}$ represents a binary variable indicating the decision to adopt damage control practices n = 1 (chemical) or 2 (non-chemical), conditional on selling to market channel j and storing maize.

The explanatory variables $\boldsymbol{v}$, price p, and risks $\boldsymbol{k}$ are included in each regression as previously discussed. In the first stage equation (2.5), however, we omit past experiences of shocks from $\boldsymbol{k}$ since market channel decisions precede the reference period for these shocks. Instead, we include yearly coefficients of variation of rainfall and temperature to account for long-term (10 years) inter-year variability. In equations (2.6) and (2.7), vector $\boldsymbol{k}$ consists of both

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traditional channel and storing can also be simplified to a probit model, we opt to employ the bivariate probit approach due to the significance of their use of chemicals, which could potentially raise food safety concerns.

[41] While Bellemare and Barrett (2006) suggest that hurdle models can be used to explicitly test whether decisions are made simultaneously or sequentially, Burke (2019) argues against it and advocates for the development of more suitable models to test for simultaneous decision making.

past experiences of shocks and monthly coefficients of variation of rainfall and temperature during the period preceding the storage decisions. We additionally include a vector $\boldsymbol{state}$, which include four binary variables representing each state, with Kaduna serving as the base state, in order to control for state-specific effects. The constants β_0, γ_0^j, and θ_0^j are included, while ε_i, ϵ_i^j, and $\xi_i^{n,j}$ represent the error terms. Particularly, in the bivariate probit model depicted in equation (2.7), the assumption is that the error terms $\xi_i^{n,j}$ follow a standard bivariate normal distribution with mean values of zero, variances of one, and a correlation coefficient, ρ.

To formulate the likelihood function for the triple-hurdle model, let $\boldsymbol{x}_1$ represent the explanatory variables in the first-stage market channel decision, $\boldsymbol{x}_2$ denote the explanatory variables in the second-stage storage decision, and $\boldsymbol{x}_3^n$ indicate the explanatory variables in the third-stage decision regarding the use of damage control practices.[42] For any given observation i, the likelihood function is derived as:

$$
\begin{aligned}
& f\left(m, z^j, y^{n,j} \middle| \boldsymbol{\beta}, \boldsymbol{\gamma}^j, \boldsymbol{\theta}^{n,j}, \boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3^n\right) \\
&= \begin{bmatrix} \Phi(\boldsymbol{x}_1\boldsymbol{\beta})\left[\Phi\left(\boldsymbol{x}_2\boldsymbol{\gamma}^{j=1}\right)\left[\Phi\left(\boldsymbol{x}_3\boldsymbol{\theta}^{j=1}\right)\right]^{1[z=1]}\left[1-\Phi\left(\boldsymbol{x}_3\boldsymbol{\theta}^{j=1}\right)\right]^{1[z=0]}\right]^{1[z=1]} \\ \left[1-\Phi\left(\boldsymbol{x}_2\boldsymbol{\gamma}^{j=1}\right)\right]^{1[z=0]} \end{bmatrix}^{1[m=1]} \times \\
& \begin{bmatrix} 1-\Phi(\boldsymbol{x}_1\boldsymbol{\beta})\begin{bmatrix}\Phi\left(\boldsymbol{x}_2\boldsymbol{\gamma}^{j=2}\right)\Phi_b(\boldsymbol{x}_3^1\boldsymbol{\theta}^{1,2}, \boldsymbol{x}_3^2\boldsymbol{\theta}^{2,2}, \rho)^{y^{1,2}y^{2,2}}\Phi_b(-\boldsymbol{x}_3^1\boldsymbol{\theta}^{1,2}, \boldsymbol{x}_3^2\boldsymbol{\theta}^{2,2}, -\rho)^{(1-y^{1,2})y^{2,2}} \\ \Phi_b(\boldsymbol{x}_3^1\boldsymbol{\theta}^{1,2}, -\boldsymbol{x}_3^2\boldsymbol{\theta}^{2,2}, -\rho)^{y^{1,2}(1-y^{2,2})}\Phi_b(-\boldsymbol{x}_3^1\boldsymbol{\theta}^{1,2}, -\boldsymbol{x}_3^2\boldsymbol{\theta}^{2,2}, \rho)^{(1-y^{1,2})(1-y^{2,2})}\end{bmatrix}^{1[z=1]} \\ \left[1-\Phi\left(\boldsymbol{x}_2\boldsymbol{\gamma}^{j=2}\right)\right]^{1[z=0]} \end{bmatrix}^{1[m=0]}
\end{aligned}
$$

where $\Phi(\cdot)$ and $\Phi_b(\cdot)$ represent the cumulative distribution functions of the standard normal and standard bivariate normal distributions, respectively.

While all parameters in the three stages can be estimated simultaneously by maximum likelihood estimation (MLE), the separable nature of the likelihood function allows for separate

[42] $\boldsymbol{x}_3^n$ simplifies to $\boldsymbol{x}_3$ for market channel $j = 1$ (modern), where a probit model is applied.

estimation of: (i) $\boldsymbol{\beta}$ through a probit regression of m on $\boldsymbol{x}_1$; (ii) $\boldsymbol{\gamma}^j$ through a probit regression of z^j on $\boldsymbol{x}_2$, using only observations that sell to market channel j; and (iii) $\boldsymbol{\theta}^{n=1,j}$ ($\boldsymbol{\theta}^{n=2,j}$) through a bivariate probit regression of $y_i^{n=1,j}$($y_i^{n=2,j}$) on $\boldsymbol{x}_3^{n=1}$($\boldsymbol{x}_3^{n=2}$), using only observations that sell to market channel j and store maize ($z = 1$). In each state, we investigate the effect of risks on traders' decisions regarding their primary market channel, storage, and damage control practices. Assuming that the error terms in the equations are not correlated conditional on all explanatory variables, the standard errors obtained from separate estimations can be used for valid statistical inference (Wooldridge, 2010). To test this assumption, we follow the Heckman test for selection bias, using the inverse mills ratio (IMR), following a three-step process outlined by Burke, Myers, and Jayne (2015). The coefficients of IMR in the second and third stages were not statistically significant, hence we fail to reject the null hypothesis that the error terms between stage one and two, as well as between stage two and three, are uncorrelated. Consequently, we proceeded to exclude IMR from both stages.

2.5 Results and Discussion

Table 2.2 presents the estimated average marginal effects for the first and second stages. Findings from the first hurdle indicate that traders' market channel selection is not associated with long-term variability in rainfall and temperature. However, we observe that traders' gender and business scale are statistically significant determinants for their market channel selection. Male traders and those operating on a larger scale exhibit a greater tendency to sell to the modern channel, a trend that could be attributed to their enhanced resource capacity and ability to invest in meeting the higher quality standards and contract requirements of this channel. From the perspective of buyers, Stringer, Sang, and Croppenstedt (2009) found that processors (in our case, the modern channel, which includes food and feed mills) regard the size of their source as the most critical factor affecting their procurement decisions. This aims to guarantee a steady supply to fulfill downstream supply commitments.

In contrast, traders affiliated with trader associations are more inclined to opt for the traditional channel. Our data reveal that these associations primarily operate within the traders' market, focusing on services that do not extend to external markets or areas where traders source or sell maize. Their key roles include providing security services, managing cleaning and waste disposal, and facilitating dispute resolution related to trading. Therefore, it is likely that membership in trader associations is particularly appealing to those who require these services and are unable to manage them independently. Consequently, these traders are less likely to have access to the modern channel. Furthermore, associations might reinforce the likelihood of their members selling to the traditional channel, leveraging their well-established relationship with it.

The state variables representing traders' locations are also statistically significant factors influencing their decision to sell to the modern channel. Given that many industrial food and feed mills are concentrated in southern Nigeria — the more affluent region and the primary maize consuming area — we observe that traders in Oyo, a southern state, are more likely to sell to the modern channel compared to those in Kaduna, the base state located in the north. In addition, traders in Plateau, a northern state proximate to the southern region and with its own food and feed production, are also more inclined to sell to the modern channel. Conversely, traders in Kano and Katsina are less likely to sell to the modern channel, indicating they are more likely to sell to the traditional channel.

Columns 2 and 3 of Table 2.2 display how the storage decisions of traders, involved in selling to the modern and traditional channels, respond to various risks. The results reveal that higher rainfall variability during the growing season is positively associated with maize storage among traders who sell mainly to the modern channel, while it exhibits a negative correlation with the storage among those primarily selling to the traditional channel. Furthermore, traders who mainly sell to the modern channel tend to store maize when confronted with higher temperature variability, while traders mainly selling to the traditional channel are less inclined to store maize under similar conditions.[43] This disparity could potentially arise because traders selling to the modern channel often operate under contractual agreements with their buyers, prompting them to store maize to compensate for potential risks induced from unfavorable weather conditions and to fulfill their contractual obligations. On the other hand, traders whose main buyers are in the traditional channel may prefer to avoid storing maize under high weather variability, as such conditions can easily lead to spoilage of stored maize. Consequently, their preference may be to promptly sell their maize to buyers in demand.

Our findings suggest a negative association between experiencing conflict shocks in the past year and storage decisions among traders primarily involved in the modern channel. One possible explanation for this observation is that conflicts significantly disrupted maize sourcing, leaving traders unable to allocate maize for storage after meeting the required quantities for their modern buyers. Conversely, for traders selling to the traditional channel, past conflict shocks do not statistically significantly relate to their storage decisions. While conflict shocks might also adversely affect their sourcing, reducing the availability of maize to store, traders may choose to store some of the sourced maize as a precautionary measure, albeit to a limited extent, given that they are less likely to have strict obligations to deliver maize to their buyers.

Furthermore, we observe a positive association between the experience of weather shocks

[43] The unconditional average marginal effects (column 1 in Appendix B, Table 2.4) reveal that weather risks do not have statistically significant effects on storage decisions when considering the overall sample, where opposite effects would be offset.

and storage decisions of these traders. This implies that traders who have encountered such adverse shocks in the past year may adopt a more cautious approach, aiming to maintain a stock in case of similar future shocks affecting maize sourcing. On the other hand, traders selling to the modern channel, who are likely to be larger and more resourceful, may be less affected by weather shocks. This could be because their sourcing is less likely to be dependent on a limited region and the occurrence of weather shocks there, as they procure maize from a wide range of regions.

Additionally, among traders whose main buyers belong to the modern market, male traders and those with formal education exhibit a higher tendency for storing maize. This inclination can be attributed to the potential advantage that male or educated traders have in terms of accessing resources or information, compared to female or uneducated traders, which enables them to adopt storage as a strategic risk management measure. Conversely, traders with longer trading experience and those engaged in other jobs are less likely to store maize. Experienced traders may have developed more efficient or streamlined sourcing strategies that lessen their need for storage. Traders engaged in alternative jobs, hence having multiple income sources, are less likely to be vulnerable to risks (Chuku and Okoye, 2009; Dercon, 2002) and may not need to invest in storage as a risk management strategy, especially when storage requires additional resources and attention.[44] Additionally, traders selling through modern channels are more inclined to engage in storage when they anticipate higher future sales prices.

On the other hand, among traders whose main buyers are in the traditional market, those who have received training in storage techniques are more likely to store. Notably, the distance to the nearest highway, used as a proxy for market access, has heterogenous associations with

[44] This may be particularly applicable to traders involved in maize farming, as they can procure maize from their own production.

storage decisions across traders selling to different market channels. Among those primarily selling to the modern channel, a longer distance to the nearest highway (i.e., limited market access) is linked to a higher likelihood of storing maize. In contrast, for traders primarily selling to the traditional market, the opposite relationship is observed, that is, a shorter distance to the nearest highway (implying improved market access) is associated with a higher propensity of storing maize. This may stem from the fact that these traders frequently engage in spot transactions; storing maize near the market could allow them to meet immediate demand while capitalizing on favorable market conditions.

We find that membership in trader associations does not affect the storage decisions of both trader groups. This could be attributed to the role of trader associations in providing services within traders' markets, rather than offering collective purchasing or transportation of maize or expanding into multi-segments or other areas. In cases where trader associations do provide such functions, membership in trader associations might have statistically significant negative associations with traders' storage decisions. This could be because these functions offer traders alternative sourcing options or greater connection with other areas, providing more robust risk management strategies.

Table 2.3 presents the estimated average marginal effects of risks on traders' adoption of damage control practices, given that they store maize. Our findings reveal that rainfall fluctuations do not have a statistically significant influence on the decisions to adopt the practices. However, higher temperature variability is adversely associated with the adoption of damage control practices among traders selling to the modern channel (column 1), as well as with the adoption of non-chemical methods among traders selling to the traditional channel (column 3), conditional on storage. One plausible explanation for this could be that traders operating in areas prone to high temperature variability are already equipped with facilities to protect stored maize from damage caused by temperature variation. Alternatively, they might perceive the risks related to temperature to be lower compared to other potential risks, such as pests or moisture.

Traders who previously encountered spoilage shocks are more likely to be cautious compared to those who did not experience such shocks. Hence, they are more likely to apply preventive treatments to stored maize, which can directly help reduce the chance of another potential spoilage shock, regardless of their main market channel. Among traders primarily engaged in the traditional channel, those who experienced conflict shocks exhibit greater likelihood of adopting both chemical and non-chemical methods. Their concern about potential disruptions may prompt them to implement dual damage control strategies to mitigate potential losses when they engage in storing. Past encounters with weather shocks are also positively correlated with the likelihood of adopting chemical treatments among these traders.

Interestingly, for all three shocks, prior experiences of the shocks exhibit a positive relationship with the use of chemicals among traders who primarily sell to the traditional channel and store maize. Conversely, among traders primarily selling to the modern channel and storing, a positive association is observed only with past spoilage shocks, which directly calls for a response to spoilage-related concerns. Given that the majority of traders primarily operate in the traditional market, the disruptions in maize trading caused by these shocks underscore a food safety challenge as the usage of chemicals has drawbacks including the development of toxic residues, which raises significant health concerns (see, for example, Akoto et al. (2013)). In contrast, the selective response of traders primarily engaged in the modern market suggests that they tend to prioritize the preservation of maize quality with minimal chemical residue. This may explain the statistically insignificant average marginal effects of weather and conflict shocks on their adoption of damage control practices.

2.6 Conclusion

This study examined the impact of various risks on the decisions of Nigerian maize wholesale traders, including their primary market channel selection, adoption of storage, and application of chemicals and/or non-chemical treatments for stored maize. The role of maize traders within the Nigerian economy is pivotal, given that the production and consumption of maize constitute a fundamental pillar of the country's food system. In particular, maize traders' storage behaviors, including the use of chemical and/or non-chemical methods, significantly impact the quantity and quality of maize accessible to consumers, and are therefore linked to issues of food security and safety.

The interplay between traders' market channel choices and their heterogenous storage behaviors is evident. Traders who predominantly sell to the modern channel are more likely to prioritize meeting the specific requirements set by their clients, which may include maintaining the quality of maize or fulfilling contractual obligations or pre-arrangements. This difference in priorities could result in distinct incentives for these traders when faced with various risks compared to those who primarily sell to traditional buyers. In this context, the adopted triple-hurdle model captures the initial stage of market channel choice, acknowledging its potential impact on subsequent decisions.

Indeed, our findings reveal heterogenous responses to risks across traders selling to different market channels. Specifically, rainfall and temperature variability in traders' business regions has opposing effects on the storage decisions between traders selling to modern and traditional buyers. For those engaging in the modern market, higher rainfall and temperature variability increases the likelihood of storing maize, whereas among those engaging more with traditional buyers, such variability reduces the likelihood of storing. This divergence can be attributed to the incentives of traders involved in the modern market to compensate for potential losses from adverse weather conditions and secure maize reserves to consistently supply their modern buyers.

Moreover, our results underscore different responses to past experiences of weather, spoilage, and conflict shocks. While encounters with these shocks exhibit statistically significant associations with the adoption of chemical treatments among traders mainly linked to traditional buyers in a positive way, only the experience of spoilage shock shows a statistically significant association with the use of damage control practices among those selling to modern buyers. Given the prevalence of traders engaged with traditional buyers, the observed rise in chemical application related to these shocks raises substantial concerns regarding the safety of maize.

There are limitations to this study. Firstly, it could be argued that traders determine their primary market channel based on the quality and quantity of maize they have after storage. While we could not test for the sequentiality of these decisions, we proceeded with the assumption that traders first decide on their primary market channels. Selecting a market channel could be considered as choosing whether to participate in a specific market, which is considered as the first stage in the double-hurdle models of market participation. Secondly, our findings do not establish causal relationships between weather risks and traders' decisions, or between experiences of shocks and traders' decisions. Potential concerns about reverse causality exist, as traders' market channels or storage behaviors may influence their exposure to risks. Additionally, traders' experiences of shocks could be endogenous, affected by unobserved trader characteristics that might also affect their market channel and storage decisions.

Nonetheless, this study provides insights into the adaptive behaviors of maize traders facing various risks. Given the growing exposure of agrifood value chains in developing countries to extreme weather events, violent conflicts and insecurity, and spoilage-related risks, this study aims to deepen our understanding of the effects of these risks and contribute to the development of more resilient agrifood systems. Comprehending how midstream actors heterogeneously respond to and navigate risks based on their distinctive characteristics, such as their primary market channel as explored here, would be crucial for designing policies that can effectively address the challenges faced by maize traders and the entire value chain.

REFERENCES

Holden, S., and R. Lunduka. 2013. "Who benefits from Malawi's targeted farm input subsidy program?" *Forum for Development Studies* 40 (1): 1–25.

Abate, G., L. Kasa, N.W. Minot, S. Rashid, S. Lemma, and J. Warner. 2015. "Maize value chain in Ethiopia structure conduct and performance." International Food Policy Research Institute (IFPRI), Washington DC.

Adams, K.M., M. Benzie, S. Croft, and S. Sadowski. 2021. "Climate Change, Trade, and Global Food Security: A Global Assessment of Transboundary Climate Risks in Agricultural Commodity Flows." SEI Report, Stockholm Environment Institute, Stockholm.

Akoto, O., H. Andoh, G. Darko, K. Eshun, and P. Osei-Fosu. 2013. "Health risk assessment of pesticides residue in maize and cowpea from Ejura, Ghana." *Chemosphere* 92(1): 67-73.

Arku, F.S., E.N. Angmor, and G.T. Adjei. 2017. "Perception and responses of traders to climate change in downtown, Accra, Ghana." *International Journal of Climate Change Strategies and Management* 9(1):56-67.

Arinloye, D.D.A., S. Pascucci, A.R. Linnemann, O.N. Coulibaly, G. Hagelaar, and O.S. Omta. 2015. "Marketing channel selection by smallholder farmers." *Journal of Food Products Marketing* 21(4):337-357.

Barrett, C. 1996. "Market Analysis Methods: Are Our Enriched Toolkits Well Suited to Enlivened Markets?" *American Journal of Agricultural Economics* 78(3): 825-829.

———. 1997. "Food Marketing Liberalization and Trader Entry: Evidence from Madagascar." *World Development* 25(5):763-777.

Belay, A., J.W. Recha, T. Woldeamanuel, and J.F. Morton. 2017. "Smallholder farmers' adaptation to climate change and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia." *Agriculture & Food Security 6*(1):1-13.

Bellemare, M.F., and C.B. Barrett. 2006. "An ordered Tobit model of market participation: Evidence from Kenya and Ethiopia." *American journal of agricultural economics* 88(2):324-337.

Brennan, D. 2003. "Price dynamics in the Bangladesh rice market: implications for public intervention." *Agricultural Economics* 29(1):15-25.

Burke, W.J. 2019. "Evidence against imposing restrictions on hurdle models as a test for simultaneous versus sequential decision making." *American Journal of Agricultural Economics* 101(5):1473-1481.

Burke, W. J., R.J. Myers, and T.S. Jayne. 2015. "A triple-hurdle model of production and market participation in Kenya's dairy market." *American Journal of Agricultural Economics* 97(4):1227-1246.

Cairns, J.E., J. Hellin, K. Sonder, J.L. Araus, J.F. MacRobert, C. Thierfelder, and B.M. Prasanna. 2013. "Adapting maize production to climate change in sub-Saharan Africa." *Food Security* 5:345-360.

Chuku, C.A., and C. Okoye. 2009. "Increasing resilience and reducing vulnerability in sub-Saharan African agriculture: Strategies for risk coping and management." *African Journal of Agricultural Research* 4(13):1524-1535.

Claytor, H.S. 2015. "Cattle Producers East of the 100th Meridian: A Study of Afforestation Adoption and Use of Pasture Management Practices." Master's thesis, University of Tennessee.

Crick, F., S.M Eskander, S. Fankhauser, and M. Diop. 2018. "How do African SMEs respond to climate risks? Evidence from Kenya and Senegal." *World Development* 108:157-168.

Dercon, S. 1995. "On Market Integration and Liberalisation: Method and Application to Ethiopia." *Journal of Development Studies* 32(1):112-143.

——. 2002. "Income risk, coping strategies, and safety nets." *The World Bank Research Observer* 17(2):141-166.

Dessalegn, G., T.S. Jayne, and J.D. Shaffer. 1998. "Market Structure, Conduct, and Performance: Constraints of Performance of Ethiopian Grain Markets." Food Security Collaborative Working Paper, Michigan State University.

Di Falco, S., M. Veronesi. and M. Yesuf. 2011. "Does adaptation to climate change provide food security? A micro-perspective from Ethiopia." *American Journal of Agricultural Economics* 93(3):829-846.

Dillon, B., and C. Dambro. 2017. "How competitive are crop markets in sub-Saharan Africa?" *American Journal of Agricultural Economics* 99(5):1344-1361.

Duniya, K. 2018. "Drivers of adoption intensity of certified maize seeds in Northern Guinea

Savannah of Nigeria: A triple hurdle model approach." 30th International Conference of Agricultural Economists, Vancouver, 28 July – 2 August.

Fafchamps, M., E. Gabre-Madhin, and B. Minten. 2005. "Increasing returns and market efficiency in agricultural trade." *Journal of Development Economics* 78(2):406-442.

Gabre-Madhin, E. Z. 2001. "Market Institutions, Transaction Costs, and Social Capital in the Ethiopian Grain Market." Research Report 124, IFPRI, Washington DC.

Goetz, S.J. 1992. "A selectivity model of household food marketing behavior in sub-Saharan Africa." *American journal of agricultural economics* 74(2):444-452.

Gómez, M.I., C.B. Barrett, L.E. Buck, H. De Groote, S. Ferris, H.O. Gao, E. McCullough, D.D. Miller, H. Outhred, A.N. Pell, and T. Reardon. 2011. "Research principles for developing country food value chains." *Science* 332(6034):1154-1155.

Haile, M.G., T. Wossen, K. Tesfaye, and J. von Braun. 2017. "Impact of climate change, weather extremes, and price risk on global food supply." *Economics of Disasters and Climate Change* 1(1):55-75.

Hastings, J.V., S.G. Phillips, D. Ubilava, and A. Vasnev. 2022. "Price Transmission in Conflict-Affected States: Evidence from Cereal Markets of Somalia." *Journal of African Economies* 31(3):272-291.

Hatzenbuehler, P.L., P.C. Abbott, and T. Abdoulaye. 2017. "Price transmission in Nigerian food security crop markets." *Journal of Agricultural Economics 68*(1):143-163.

Herrero, M., P. Havlik, J. McIntire, A. Palazzo, and H. Valin. 2014. *African Livestock Futures: Realizing the potential of livestock for food security, poverty reduction and the environment in Sub-Saharan Africa.* Office of the Special Representative of the UN Secretary General for Food Security and Nutrition and the United Nations System Influenza Coordination (UNSIC), Geneva, Switzerland.

Hoffmann, V., and C. Moser. 2017. "You get what you pay for: the link between price and food safety in Kenya." *Agricultural Economics* 48(4):449-458.

Holden, S.T., and J. Quiggin. 2017. "Climate risk and state-contingent technology adoption: shocks, drought tolerance and preferences." *European Review of Agricultural Economics* 44(2):285-308.

Jensen, K.L., D.M. Lambert, C.D. Clark, C. Holt, B.C. English, J.A. Larson, T.E. Yu, and C.

Hellwinckel. 2015. "Cattle Producers' Willingness to Adopt or Expand Prescribed Grazing in the United States." *Journal of Agricultural and Applied Economics* 47(2):213-242.

Jones, P.G., and P.K. Thornton. 2003. "The potential impacts of climate change on maize production in Africa and Latin America in 2055." *Global environmental change* 13(1):51-59.

Kabubo-Mariara, J., and R. Mulwa. 2019. "Adaptation to climate change and climate variability and its implications for household food security in Kenya." *Food security* 11(6):1289-1304.

Kadjo, D., J. Ricker-Gilbert, and C. Alexander. 2016. "Estimating price discounts for low-quality maize in sub-Saharan Africa: evidence from Benin." *World Development* 77:115-128.

Kadjo, D., J. Ricker-Gilbert, G. Shively, and T. Abdoulaye. 2020. "Food safety and adverse selection in rural maize markets." *Journal of Agricultural Economics* 71(2):412-438.

Knudsen, O., and J. Nash. 1990. "Domestic price stabilization schemes in developing countries." *Economic development and cultural change* 38(3):539-558.

Lichtenberg, E., and D. Zilberman. 1986. "The econometrics of damage control: why specification matters." *American Journal of Agricultural Economics* 68(2):261-273.

Liverpool-Tasie, L.S.O., and C.M. Parkhi. 2021. "Climate risk and technology adoption in the midstream of crop value chains: evidence from Nigerian maize traders." *Journal of Agricultural Economics* 72(1):158-179.

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.

Liverpool-Tasie, L.S.O., N.S. Turna, O. Ademola, A. Obadina, and F. Wu. 2019. "The occurrence and co-occurrence of aflatoxin and fumonisin along the maize value chain in southwest Nigeria." *Food and Chemical Toxicology* 129:458-465.

Mabuza, M.L., G. Ortmann, and E. Wale. 2014. "Effects of transaction costs on mushroom producers' choice of marketing channels: implications for access to agricultural markets in Swaziland." *South African Journal of Economic and Management Sciences* 17(2):207-219.

Mehdi, M., M. Ashfaq, S. Hassan, and M. Abid. 2019. "Effect of marketing channel choice on the profitability of citrus farmers: evidence form Punjab-Pakistan." *Pakistan Journal of Agricultural Sciences* 56(4):1003-1011.

Mertz, O., K. Halsnæs, J.E. Olesen, and K. Rasmussen. 2009. "Adaptation to climate change in developing countries." *Environmental management* 43(5):743-752.

Michelson, H., T. Reardon, and F. Perez. 2012. "Small farmers and big retail: trade-offs of supplying supermarkets in Nicaragua." *World Development* 40(2):342-354.

Minten, B. and S. Kyle. 1999. "The effect of distance and road quality on food collection, marketing margins, and traders' wages: evidence from the former Zaire." *Journal of Development Economics* 60(2):467-495.

Mmbando, F.E., E.Z. Wale, and L.J. Baiyegunhi. 2017. "The welfare impacts of market channel choice by smallholder farmers in Tanzania." *Development in Practice* 27(7):981-993.

Muyanga, M., D. Tschirley, T.A. Reardon, T.S. Jayne, F. Meyer, L.S.O. Liverpool-Tasie, and T. Davids. 2019. "Rural and Agrifood Systems in Transforming Economies in Africa and Asia." Policy Research Brief on Synthesis Report III, Feed the Future Innovation Lab for Food Security Policy, Michigan State University.

Müller, C., W. Cramer, W.L. Hare, and H. Lotze-Campen. 2011. "Climate change risks for African agriculture." *Proceedings of the National Academy of Sciences* 108(11):4313-4315.

Myers, R.J. 2013. "Evaluating the effectiveness of inter-regional trade and storage in Malawi's private sector maize markets." *Food Policy* 41:75-84.

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

Negi, D.S., P.S. Birthal, D. Roy, and M.T. Khan. 2018. "Farmers' choice of market channels and producer prices in India: Role of transportation and communication networks." *Food Policy* 81:106-121.

Newbery, D.M.G., Stiglitz, J.E., 1981. *The Theory of Commodity Price Stabilization*. Clarendon

Press, Oxford.

Pachauri, R. K., M.R. Allen, V.R. Barros, J. Broome, W. Cramer, R. Christ, J.A. Church, L. Clarke, Q. Dahe, P. Dasgupta, and N.K. Dubash. 2014. *Climate change 2014: Synthesis report.* Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change, p. 151.

Stringer, R., N. Sang, and A. Croppenstedt. 2009. "Producers, processors, and procurement decisions: the case of vegetable supply chains in China." *World development* 37(11) :1773-1780.

Ravallion, M. 1986. "Testing Market Integration." *American Journal of Agricultural Economics* 68(1):102-109.

Reardon, T. 2015. "The hidden middle: the quiet revolution in the midstream of agrifood value chains in developing countries." *Oxford Review of Economic Policy* 31(1):45-63.

Reardon, T., K. Chen, B. Minten, and L. Adriano. 2012. *The quiet revolution in staple food value chains: Enter the dragon, the elephant, and the tiger*. Asian Development Bank.

Reardon, T., L.S.O Liverpool-Tasie, and B. Minten. 2021. "Quiet Revolution by SMEs in the midstream of value chains in developing regions: wholesale markets, wholesalers, logistics, and processing." *Food Security* 13(6):1577-1594.

Reardon, T. and D. Zilberman. 2018. "Climate smart food supply chains in developing countries in an era of rapid dual change in agrifood systems and the climate." In L. Lipper, N. McCarthy, D. Zilberman, S. Asfaw, and G. Branca, ed. *Climate smart agriculture*. Springer, pp. 335 –351.

Reuveny, R. 2000. "The trade and conflict debate: A survey of theory, evidence and future research." *Peace Economics, Peace Science and Public Policy* 6(1):23-49.

Sanou, A., L.S.O. Liverpool-Tasie, V. Caputo, and J. Kerr. 2021. "Introducing an aflatoxin-safe labeling program in complex food supply chains: Evidence from a choice experiment in Nigeria." *Food Policy* 102:102070.

Singbo, A., F. Badolo, J. Lokossou, and H. Affognon. 2021. "Market participation and technology adoption: An application of a triple-hurdle model approach to improved sorghum varieties in Mali." *Scientific African* 13:e00859.

Stathers, T., R. Lamboll, and B.M. Mvumi. 2013. "Postharvest agriculture in changing climates:

its importance to African smallholder farmers." *Food Security* 5(3):361-392.

Staatz, J.M., J. Dioné, and N.N. Dembele. 1989. "Cereals market liberalization in Mali." *World Development* 17(5):703-718.

Stokeld, E., S.A. Croft, J.M. Green, and C.D. West. 2020. "Climate change, crops and commodity traders: subnational trade analysis highlights differentiated risk exposure." *Climatic change* 162(2):175-192.

Suleiman, R.A., K.A. Rosentrater, and C.J. Bern. 2013. "Effects of deterioration parameters on storage of maize." American Society of Agricultural and Biological Engineers (p.1), Kansas City, Missouri, 21–24 July.

Tefera, T. 2012. "Post-harvest losses in African maize in the face of increasing food shortage." *Food security* 4(2):267-277.

United Nations, Food and Agriculture Organization (FAO). 2006. *Food security. Policy Brief, Issue 2*. Agriculture and Development Economics Division.

—–. 2018. *Agricultural policy incentives in sub-Saharan Africa in the last decade (2005–2016), Monitoring and Analysing Food and Agricultural Policies (MAFAP) synthesis study*. Agricultural Development Economics Division.

Williams, J.C., and B. Wright. 1991. *Storage and Commodity Markets*. Cambridge University Press, Cambridge.

Vandeplas, A., B. Minten, and J.F. Swinnen. 2009. On food quality in domestic markets of developing economies. International Association of Agricultural Economists Conference, Beijing, China, 16–22 August.

Wooldridge, J.M. 2010. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Wright, B.D., and J.C. Williams. 1982. "The economic role of commodity storage." *The Economic Journal* 92(367):596-614.

Xaba, B.G., and M.B. Masuku. 2013. "Factors affecting the choice of marketing channel by vegetable farmers in Swaziland." *Sustainable Agriculture Research* 2(1).

Zhang, M., M. Kagatsume, and J. Yu. 2014. "Market channel choice and its impact on farm household income: A case study of 243 apple farmers in Shaanxi province, China." *Japan Agricultural Research Quarterly: JARQ* 48(4):433-441.

APPENDIX A. TABLES AND FIGURES

Table 2.1 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 otherwise	1,109	.64	.48
Chemical	1 if applied chemicals to stored maize, 0 otherwise	711	.20	.40
Non-chemical	1 if applied non-chemical methods to stored maize, 0 otherwise	711	.05	.22
Modern channel	1 if mainly sold to a modern channel, 0 if mainly sold to a traditional channel	1,057	.23	.42
*Risks (**k**)*				
CV of rainfall	Coefficient of variation of monthly rainfall (mm) in traders' base region, from 4/2021 to 7/2021	1,107	.94	.34
CV of temperature	Coefficient of variation of monthly temperature (°C) in traders' base region, from 4/2021 to 7/2021	1,107	.11	.02
Past weather shock	1 if experienced weather shocks from 8/2020 to 7/2021, 0 otherwise	1,109	.13	.34
Past spoilage shock	1 if experienced spoilage shocks from 8/2020 to 7/2021, 0 otherwise	1,109	.03	.17
Past conflict shock	1 if experienced conflict shocks from 8/2020 to 7/2021, 0 otherwise	1,109	.49	.5
*Explanatory variables (**v**)*				
Male	1 if trader is male, 0 if female	1,109	.88	.33
Formal education	1 if formally educated, 0 otherwise	1,109	.71	.45
Years of trading	Number of years as a maize wholesale trader	1,098	20.00	8.74
Storage training	1 if has ever received storage technique training, 0 otherwise	1,109	.02	.13
Large scale	1 if has large monthly sales over 32 tons during the high trading season, 0 otherwise	961	.25	.43
Distance to highway	Km distance from trader's base region to the nearest highway	1,024	4.84	9.01
Trader association	1 if has membership in maize business organizations/groups, 0 otherwise	1,109	.56	.50
Other job	1 if engaged in other income-generating jobs, 0 otherwise	1,109	.14	.35
Prices (p)				
Maize sales price	Sales price of maize for the last transaction (1,000 Naira/ton)	988	196.63	108.32

Figure 2.1 The triple-hurdle approach

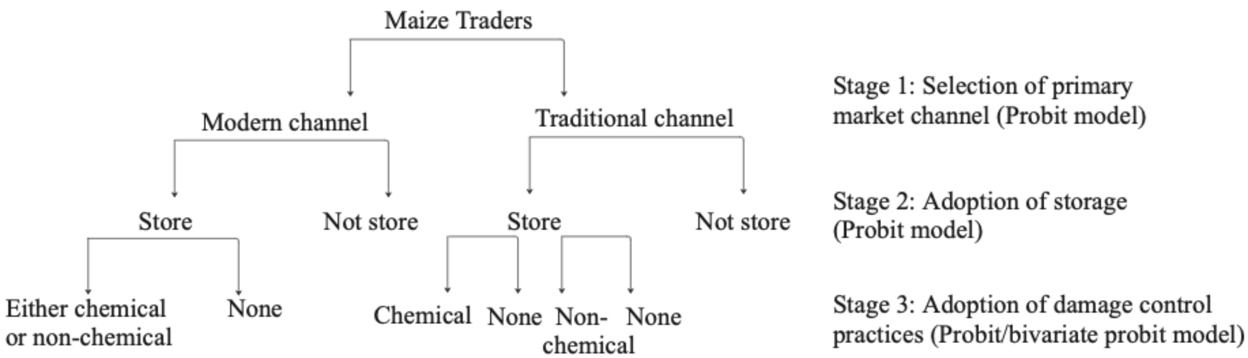

Table 2.2 Average marginal effects of risks on main market channel choice and storage

	First hurdle	Second hurdle	
VARIABLES	(1) Modern channel =1	(2) Storage =1 | Modern channel	(3) Storage =1 | Traditional channel
Male (0/1)	0.152***	0.163**	0.103
	(0.042)	(0.075)	(0.096)
Formal education (0/1)	0.041	0.292***	-0.037
	(0.048)	(0.070)	(0.045)
Years of trading	-0.004	-0.010***	-0.001
	(0.003)	(0.003)	(0.003)
Storage training (0/1)	-0.021	0.051	0.300***
	(0.111)	(0.097)	(0.024)
Large scale (0/1)	0.179***	-0.077	0.059
	(0.045)	(0.064)	(0.058)
Distance to highway (km)	0.001	0.007**	-0.006***
	(0.002)	(0.003)	(0.002)
Trader Association (0/1)	-0.091**	0.067	0.027
	(0.045)	(0.061)	(0.047)
Other job (0/1)	0.012	-0.407***	-0.002
	(0.054)	(0.072)	(0.052)
Maize sales price (Naira/ton)	1.08e-07	1.85e-06***	1.26e-07
	(1.24e-07)	(6.32e-07)	(1.81e-07)
CV of rainfall (yearly)	-1.333	-	-
	(0.932)		
CV of temperature (yearly)	-21.33	-	-
	(28.74)		
CV of rainfall (monthly)	-	1.436**	-0.329*
		(0.713)	(0.194)
CV of temperature (monthly)	-	18.71***	-17.16***
		(4.023)	(5.521)
Past weather shock (0/1)	-	-0.041	0.107**
		(0.080)	(0.055)
Past spoilage shock (0/1)	-	0.013	0.137
		(0.121)	(0.106)
Past conflict shock (0/1)	-	-0.141**	0.072
		(0.058)	(0.051)
Kano State (0/1)	-0.294***	-0.304	0.217*
	(0.105)	(0.239)	(0.117)
Katsina State (0/1)	-0.159**	0.290**	0.152*
	(0.072)	(0.116)	(0.088)
Oyo State (0/1)	0.649***	0.610***	-0.570***
	(0.138)	(0.025)	(0.109)
Plateau State (0/1)	0.406***	-0.452***	-0.636***
	(0.094)	(0.087)	(0.023)
Observations	839	197	642

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.3 Average marginal effects of risks on damage control practices[45]

	Third hurdle		
VARIABLES	(1) Use of damage control practices =1 | Modern channel and storage	(2) Use of chemicals =1 | Traditional channel and storage	(3) Use of non-chemical methods =1 | Traditional channel and storage
Male (0/1)	0.015	-0.092	-0.215*
	(0.052)	(0.084)	(0.116)
Formal education (0/1)	0.100**	-0.017	0.041**
	(0.042)	(0.036)	(0.020)
Years of trading	-0.001	0.002	0.002
	(0.003)	(0.002)	(0.001)
Large scale (0/1)	0.101*	0.068	0.073
	(0.060)	(0.050)	(0.049)
Distance to highway (km)	-0.032***	0.001	0.003**
	(0.0082)	(0.002)	(0.002)
Trader Association (0/1)	0.140**	-0.059	-0.035
	(0.057)	(0.039)	(0.024)
Other job (0/1)	-	0.085*	0.087*
		(0.051)	(0.050)
Maize sales price (Naira/ton)	-4.18e-07	7.53e-08	1.33e-07*
	(5.26e-07)	(3.09e-07)	(7.33e-08)
CV of rainfall (monthly)	-0.786	-0.049	-0.151
	(0.497)	(0.141)	(0.103)
CV of temperature (monthly)	-40.19***	0.534	-6.724**
	(14.33)	(4.748)	(3.252)
Past weather shock (0/1)	0.035	0.127**	0.012
	(0.065)	(0.054)	(0.027)
Past spoilage shock (0/1)	0.654***	0.442***	0.136*
	(0.027)	(0.135)	(0.080)
Past conflict shock (0/1)	0.074	0.077*	0.056*
	(0.052)	(0.044)	(0.030)
Kano State (0/1)	-0.175***	0.225***	-0.078
	(0.022)	(0.047)	(0.077)
Katsina State (0/1)	-0.234***	0.038	-0.084**
	(0.029)	(0.108)	(0.043)
Oyo State (0/1)	-0.217***	0.260	-0.088***
	(0.021)	(0.566)	(0.015)
Plateau State (0/1)	-0.037	-0.141***	-0.055***
	(0.046)	(0.018)	(0.015)
Observations	101	448	448

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[45] The variable 'Storage training (0/1)' was excluded from all third-stage regressions due to insufficient variation. Similarly, 'Other job (0/1)' was excluded from the third-stage regression for traders selling to the modern channel and store (column 1).

APPENDIX B. SUPPLEMENTARY MATERIALS

Table 2.4 Unconditional average marginal effects of risks

	Second hurdle	Third hurdle	
VARIABLES	(1) Storage =1	(2) Use of chemicals =1	(3) Use of non-chemical methods =1
Male (0/1)	0.198**	-0.009	-0.147
	(0.084)	(0.036)	(0.093)
Formal education (0/1)	0.003	-0.027	-0.005
	(0.046)	(0.024)	(0.015)
Years of trading	-0.003	0.001	0.0001
	(0.002)	(0.001)	(0.001)
Storage training (0/1)	0.157	-0.094***	0.003
	(0.101)	(0.011)	(0.059)
Large scale (0/1)	0.068	0.044*	0.034*
	(0.051)	(0.026)	(0.020)
Distance to highway (km)	-0.003	0.001	-1.51e-05
	(0.002)	(0.002)	(0.001)
Trader Association (0/1)	0.037	-0.036	-0.009
	(0.044)	(0.024)	(0.015)
Other job (0/1)	-0.154***	0.081**	0.020
	(0.053)	(0.035)	(0.023)
Maize sales price (Naira/ton)	1.96e-07	-9.46e-09	4.85e-08
	(2.76e-07)	(1.32e-07)	(3.48e-08)
CV of rainfall (monthly)	0.184	0.011	-0.045
	(0.173)	(0.093)	(0.063)
CV of temperature (monthly)	-0.960	1.284	-2.763
	(3.947)	(2.323)	(1.792)
Past weather shock (0/1)	-0.023	0.045	-0.023
	(0.060)	(0.029)	(0.014)
Past spoilage shock (0/1)	0.123	0.178*	0.086
	(0.165)	(0.094)	(0.103)
Past conflict shock (0/1)	-0.006	0.012	0.027
	(0.045)	(0.024)	(0.018)
Kano State (0/1)	0.177*	0.168***	-0.023
	(0.102)	(0.061)	(0.031)
Katsina State (0/1)	0.178**	0.023	-0.041**
	(0.088)	(0.067)	(0.019)
Oyo State (0/1)	0.345**	0.443	-0.071***
	(0.148)	(0.382)	(0.018)
Plateau State (0/1)	-0.194*	-0.061*	-0.053***
	(0.108)	(0.032)	(0.019)
Observations	882	882	882

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

CHAPTER 3:

ADDRESSING CONFLICT AND WEATHER SHOCKS IN AGRIFOOD VALUE CHAINS: POLICY PREFERENCES OF NIGERIAN MAIZE TRADERS

3.1 Introduction

Agrifood value chains in developing countries have undergone rapid growth and transformation in recent decades, extending across larger geographical areas and involving more actors. This significant change in a relatively short period necessitates an urgent understanding of these transformations and the development of supportive policies and infrastructure to adapt to the evolving nature of the value chains (Barrett et al., 2019; Tadesse and Badiane, 2020; Vos and Cattaneo, 2020). This need becomes particularly evident as the expansion of value chains is likely to increase the exposure of participating actors to risks stemming from various factors such as climate change, insecurity, and violent conflicts.

Within agrifood value chains, actors in the middle segment, including transporters, wholesalers, and processors, play a pivotal role as they are vital links between the upstream and downstream components. For example, in Nigeria, maize wholesale traders serve as a major market outlet for farmers; in turn, these traders supply maize to approximately 75% of the Nigerian population (Liverpool-Tasie et al., 2017). Reardon et al. (2012) underscore that midstream actors make substantial contributions to staples value chains, constituting 30-40% of the total value added.

Despite the pivotal role of midstream actors and the disruptions to their activities caused by various risks and shocks, there is limited understanding of their challenges and policies aimed at addressing them. Furthermore, discussions surrounding policies supportive of the resilient and effective functioning of agrifood value chains have primarily focused on hard infrastructure policy measures (e.g., dams and electrification), with minimal attention given to soft infrastructure policy measures (e.g., financial services and information technologies) (Ghosal, 2013; Rocker, 2019). Nonetheless, the needs of agrifood value chain actors regarding both hard and soft infrastructure have not been thoroughly investigated. Moreover, their perspectives on existing policies promoting infrastructure, as well as their preferences for potential policies, remain unexplored.

This study investigates the perspectives of midstream actors on policy interventions aimed at addressing the potential risks and shocks faced by agrifood value chains. Specifically, we examine the policy preferences of small and medium-sized Nigerian maize wholesale traders in response to policies addressing common shocks in Nigeria. These shocks include extreme weather events such as floods and droughts, as well as conflict (or insecurity) incidents such as those involving Boko Haram, herder-farmer conflicts, armed robbery or banditry, and kidnapping. We examine various policy options for addressing these shocks, encompassing safety and energy infrastructure-related policies as hard infrastructure policy measures, along with financial, informational, and security policies as soft infrastructure policy measures.

We employ the Best-Worst Scaling (BWS) approach to assess maize trader's relative preferences for various policy options, while exploring traders' trade-offs between them (Lusk and Briggeman, 2009), especially hard and soft infrastructure policy measures. The BWS method, initially introduced by Finn and Louviere (1992), has found wide application in the agricultural marketing literature to evaluate consumer preferences for food values (Bazzani et al., 2018; Costanigro, Appleby, and Menke, 2013; Lister et al., 2017; Lusk and Briggeman, 2009). It has also been widely employed in the agricultural and food policy literature to examine preferences for food production practices (McKendree, Tonsor, and Wolf, 2018) and policy preferences of input suppliers (Maredia et al., 2022), farmers (Ola and Menapace, 2020; Ortega et al., 2015; Wolf and Tonsor, 2013; Maredia et al., 2022; Mason et al., 2019), consumers (Caputo and Lusk, 2019; Stone, Costanigro, and Goemans, 2018), and other agricultural sector stakeholders such as research organization and government (Mason et al., 2019). However, there is a notable gap in the existing literature regarding the assessment of policy preferences among midstream actors in agrifood value chains. One exception is Maredia et al.'s (2022) examination of crop millers and traders' preferences for COVID-19 pandemic recovery policies.

This study contributes to the agricultural and food policy literature in three ways. First, while the policy preferences of upstream and downstream actors have been extensively studied, relatively little attention has been given to the preferences of midstream actors. We contribute to this thin literature by presenting evidence from maize wholesale traders in Nigeria, one of the largest maize-producing countries in Africa (USDA, 2022). Policies derived from understanding and addressing the assessment and needs of midstream actors have the potential to mitigate the effects of shocks on their activities, thereby benefiting the entire value chain, particularly farmers upstream and consumers downstream.

Second, we offer new insights into addressing prevalent and rising shocks in agrifood value chains. Extreme weather events and violent conflicts 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 influence maize traders. 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 and conflict shocks.

Third, we explore heterogeneity in policy preferences based on midstream actors' characteristics. The preferences of these actors regarding various policy options, including both hard and soft infrastructure policy measures, are potentially shaped by their demographic and business traits, as well as their prior experience with shocks. Through our analysis of maize traders' preferences for each type of shock and across different subgroups, we underscore the importance of tailoring policy responses to the specific nature of shocks and characteristics of traders.

Our findings reveal that regarding conflict shocks, maize traders prioritize soft infrastructure policy measures, such as enhanced security services. On the other hand, their priority shifts to hard infrastructure policy measures, such as improved flood-proof infrastructure, in response to weather shocks. Subgroups of traders, categorized by gender, business scale, education, geographic region, and prior experience with shocks exhibit heterogeneous policy preferences. For example, despite expectations that female traders, often facing resource constraints, would prioritize financial assistance such as cash relief, we find that concerning both conflict and weather shocks, they prioritize physical infrastructure more as a preventive measure, likely due to their heightened vulnerability to shocks. Furthermore, since northern Nigeria is the primary maize-producing region, the frequent occurrence of violent conflicts in this area affects southern traders who rely on the northern region for sourcing maize, leading to distinct policy preferences across northern and southern trader groups.

3.2 Background and Policy Identification

Jaffee, Siegel, and Andrews (2010) developed a conceptual framework for identifying risks within agricultural value chains, as well as for assessing participating actors' exposure to, and potential losses from, these risks. Primary risks encountered by economic agents throughout agricultural value chains include extreme weather events such as floods, droughts, and hurricanes, biological and environmental risks like crop diseases, risks related to changing market conditions, as well as logistical and infrastructural risks involving conflicts and physical destruction of infrastructure. Of particular focus in our study are weather and conflict-related shocks, which are increasingly prevalent in many countries, including Nigeria (Nogales and Oldiges, 2023; Ojo, Oyewole, and Aina, 2023).

Weather and conflict shocks have the potential to impact various stages of the maize value chain and midstream actors, especially wholesale traders. For example, floods or droughts in the upstream farm area can affect the production and availability of maize, subsequently influencing traders' maize purchases. Floods, in particular, can damage traders' maize storage by increasing the likelihood of pest infestations or mold growth (Liverpool-Tasie and Parkhi, 2021), and they can also disrupt the transportation of maize by causing road washouts. Violent conflicts can similarly disrupt entire value chains, from production areas to transportation routes and markets, thereby limiting traders' ability to buy, transport, store, and sell maize. Vargas, Reardon, and Liverpool-Tasie (2023) observed that between August 2020 and July 2021, 13% of Nigerian maize wholesale traders in the northern region and 26% of traders in the southern region experienced disruptions caused by floods and droughts. Additionally, nearly half of the traders were affected by violent conflicts during the same period.

The set of risk management measures proposed by Jaffee, Siegel, and Andrews (2010) includes, but is not limited to: (i) financial instruments (e.g., credit, savings, and insurance); (ii) enterprise management practices (e.g., farm and firm diversification practices); (iii) technology development and adoption (e.g., postharvest technology and information technology); (iv) public policy and programs (e.g., law enforcement and protection of property and human rights); and (v) infrastructure investment (e.g., transport and communication infrastructure). We examined these five instruments within the Nigerian context, drawing from government documents and inputs provided by Nigerian maize traders. Consequently, we 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 categorized into two broad types: soft and hard infrastructure policy measures. The detailed policy options for conflict and weather shocks are presented in Table 3.1.

Soft infrastructure policy options include policies to improve access to financial services, information technology, and security operations. Financial policies involve providing (ex-post) cash assistance to traders who suffered losses due to conflict or weather shocks; enhancing access to (ex-ante) insurance coverage to compensate for potential losses due to these shocks; and facilitating access to loans for investing in technologies such as security cameras and better storage facilities, to help prevent losses from conflict and weather shocks, respectively. Policies targeting improved access to information technology include the establishment of early warning systems and call centers that provide real-time information on route safety. These measures can assist traders in avoiding unsafe routes where conflicts are ongoing or imminent, as well as flooded routes, and in using alternative routes. Furthermore, information technology policies involve strengthening traders' capacity through training on risk management technologies, such as strategies to diversify suppliers in response to conflict shocks and measures to prevent mold or rodent growth following weather shocks. Additionally, enhancing security services (e.g., police, security personnel, or surveillance systems) along roads and in market or warehouse areas is included to address conflict shocks.

On the other hand, hard infrastructure policy options encompass the construction or improvement of road infrastructure, such as building or improving dams, culverts, or drainage systems on roads to prevent or minimize flooding (for weather shocks); and the installation of protective hardware (e.g., concrete barriers for conflict shocks and flood barriers, sandbags, or tarps for weather shocks) for markets and warehouses. Additionally, it includes investments in energy infrastructure to provide a more reliable electricity supply, for purposes such as lighting to improve safety and security in response to conflict shocks, as well as for ensuring the reliable operation of temperature-controlled warehouses to preserve stored maize in response to weather shocks.

3.3 Data and Survey Design

We designed a survey to collect data from a sample of Nigerian maize wholesale traders, including their demographic and business characteristics, as well as their relative preferences for the aforementioned policy options to address conflict and weather shocks. Between May and August 2023, we conducted in-person interviews with a total of 300 maize wholesale traders, selected as a sub-sample from a previous survey involving maize traders.

The initial maize trader survey in Nigeria was conducted in 2017, including 1,405 maize traders from 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’, comprising traders with maize sales above 32 tons during a typical month in the high maize trading season (from August to February), and the ‘small trader stratum’, consisting of those with maize sales below 32 tons during the same period. The cutoff of 32 tons represents the average volume of maize traded during this period across all the regional markets in the study states. 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, from among those interviewed in 2021, we randomly selected 60 maize traders from each of the five states, totaling 300 traders.[46]

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

Balanced Incomplete Block Designs (BIBDs) are frequently used in experimental designs for Case 1 (object case) BWS surveys, where a set of objects or items (i.e., policy options in this study) is measured (Bazzani et al., 2018; Louviere, Flynn, and Marley, 2015).[47] Balance is achieved by ensuring that each choice set contains an equal number of objects 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 with equal frequency across the choice sets. However, generating a BIBD may lead to a large number of choice sets, potentially causing respondent fatigue (Bazzani et al., 2018). Implementing a BIBD in our case would result in 18 BWS choice sets regarding conflict shock policies and 14 BWS choice sets regarding weather shock policies, each containing four different policy options.

Therefore, we opted to use a generalized Cyclic Incomplete Block Design (CIBD) (Jarrett

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[46] 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.

[47] Case 2 (profile case) and Case 3 (multi-profile case) BWS surveys involve measuring attribute levels and profiles, respectively.

and Hall, 1978; John, 1981), which is a class of Partially (or nearly) Balanced Incomplete Block Designs (PBIBDs) relaxing the orthogonality requirement. While all pairs of objects are estimated with the same accuracy in BIBDs, PBIBDs help in reducing the number of required choice sets at the cost of some pairs of objects having different efficiency from other pairs of objects. Among different types of PBIBDs, CIBDs are easy to construct, possess good statistical properties, and their analysis is the same as the analysis of BIBDs (Lawson, 2014). In our case, the design resulted in nine BWS choice sets for conflict shock policies and eight BWS choice sets for weather shock policies, each containing four policy options. Each of the nine conflict shock policy options is repeated four times across the nine conflict shock choice sets. Similarly, each of the eight weather shock policy options appears four times across the eight weather shock choice sets. In addition, each conflict shock policy option has four first associates and four second associates, while each of weather shock policy option has five first associates and two second associates. First associates refer to a pair of policy options that occur together in two choice sets, while second associates are a pair of policy options that occur together in one choice set. The design maximizes D-efficiency, which assesses the goodness of a design compared to orthogonal designs with optimal efficiency (Kuhfeld, 2005).

In each BWS choice set, traders were asked to select the best (most preferred) and worst (least preferred) policy option. Examples of BWS choice sets for conflict and weather shock policies are provided in Figure 3.1.

3.4 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 as the difference between the best and worst counts. The policy option 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 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:

$$U_{nji} = \beta_j - \beta_i + \varepsilon_{nji}, \tag{3.1}$$

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 an 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:

$$P_{nji} = \int_{\beta} \prod_{s=1}^{S} \frac{e^{[\beta_{njs} - \beta_{nis}]}}{\sum_{m=1}^{J} \sum_{k=1}^{J} e^{[\beta_{nms} - \beta_{nks}] - J}} f(\beta_n) d\beta_n, \tag{3.2}$$

where $f(\beta_n)$ denotes the density function of the importance parameters β_n to be estimated, which we assume to be normally distributed 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 ($\widehat{\beta_n}$), we derive the share of preferences for each policy option m (SOP_m) using the bootstrapping method by Krinsky and Robb (1986):

$$SOP_m = \frac{e^{\widehat{\beta}_m}}{\sum_{k=1}^{J} e^{\widehat{\beta}_k}} \tag{3.3}$$

The share of preferences (SOP) 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 in this study (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 more preferred than policy i. We report the mean and standard errors of the share of preferences for each policy option.

Additionally, we compute the individual-specific share of preferences for each policy option 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 policy options 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 policy options 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 policy preferences. The FML model is represented as the conditional mean of the individual share of preferences as follows, with the coefficient of a base policy normalized to zero (Mullahy, 2015):

$$E(sop_{nm}|\boldsymbol{x}_n) = \frac{e^{\alpha_m x_n}}{\sum_{k=1}^{J} e^{\alpha_k x_n}} \tag{3.4}$$

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

3.5 Results and Discussion

The characteristics of maize traders are summarized in Table 3.2.[48] On average, traders are 47 years old, and approximately 20% of them are female. About 65% of traders have completed formal education, either at the primary, secondary, or post-secondary 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 traders (about 90%) did not engage in other income-generating jobs between August 2020 and July 2021. Following our sampling strategy, 80% of traders are located in the northern region, which includes 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. Additionally, only 15% and 3% of traders in our sample experienced conflict shocks and weather shocks, respectively, between August 2020 and July 2021.

Preferences for Conflict and Weather Shock Policies

To estimate the RPL model, we used *Real-time safety info* as the reference for conflict shock policies and *Real-time weather info* as the reference for weather shock policies, guided by

[48] Nine traders transitioned out of maize trading between the 2021 maize trader survey and the current 2023 survey. Although these traders are no longer engaged in maize trading, we retained them for participation in the policy preference BWS choice sets, without collecting additional demographic or maize business data.

the lowest BW scores (Appendix B, Table 3.9). The results of the correlated RPL models are reported in Tables 3.3 and 3.4.[49] 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 contrasts with 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. This disparity may suggest a nuanced response to crises: while traders in Myanmar may have leaned towards government-led, systematic initiatives for the unprecedented pandemic, Nigerian traders, somewhat accustomed to recurrent conflict and weather shocks, may favor the flexibility of cash to address their various needs.

In addition to the widely favored cash relief option among maize traders, their 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 (Table 3.3), traders tend to place a higher emphasis on soft infrastructure policy measures aimed at ensuring a secure environment (i.e., *Improved road security* and *Improved market/warehouse security*), followed by hard infrastructure measures (i.e., *Improved market/warehouse safety infrastructure* and *Improved market/warehouse lighting*). It is likely that traders facing conflict shocks, which often involve threats from human actions, are inclined to emphasize security measures that provide immediate protection against potential harm and ensure a safe business environment.

On the contrary, when encountering weather shocks (Table 3.4), traders predominantly prioritize hard infrastructure policies such as improved road infrastructure and market/warehouse

[49] 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. Correlated models allow for correlations among utility coefficients (or importance parameters), which can arise from various sources, including scale heterogeneity (Hess and Train, 2017).

flood protection infrastructure. These are followed by financial services-related policies (i.e., *Loans for weather tech* and *Weather insurance*), categorized as soft infrastructure policies. This shift in preference could possibly be attributed to the physical and logistical challenges posed by adverse weather shocks, necessitating more tangible and enduring solutions to protect their trading activities. Notably, hard infrastructure on the road (26.8% SOP) is considered more crucial than that in the market/warehouse area (16% SOP), indicating that disruptions in transportation is likely to present a considerable obstacle for traders.

Regarding both conflict and weather shocks, the establishment of call centers for real-time information, which served as the reference policy, emerges as the least preferred option. This may reflect a lack of trust in the feasibility of obtaining real-time information given the current state of information technology in the country. In addition to the real-time information policy option, *Conflict training* and *Loans for security* rank among the lowest three policies in response to conflict shocks. The low interest in training could be attributed to a perceived lack of value in information provided by the government relative to traders' own experiences and networks. Similarly, *Weather training* and *Improved market/warehouse electricity* occupy the bottom three positions in response to weather shocks. This lack of interest in electricity infrastructure may stem from a generally low-level trust in the government's capability to implement such improvements.

Factors Influencing Policy Preferences

The application of the fractional multinomial logit (FML) model enhances our understanding of the determinants shaping maize traders' policy preferences. Tables 3.5 and 3.6 present the average marginal effects of traders' characteristics on the shares of preferences for conflict and weather shock policies, respectively. Notable findings pertain to the gender, business scale, education, and regional disparity among traders.[50]

As observed from both current and previous datasets from 2021, the Nigerian maize wholesaling sector is predominantly male-dominated, with male traders constituting approximately 80% of traders in major maize-producing and consuming states.[51] Moreover, the maize trading sector reflects the widely documented gender disparity in Nigeria, where women typically face greater social barriers (Adebayo and Akanle, 2014) and resource constraints than men (see, for example, Ajadi, 2015; Muoghalu and Abrifor, 2012), as well as having limited access to agricultural inputs compared to men (Uduji and Okolo-Obasi, 2018). Male traders tend to possess greater resources, often operating on a larger and more extensive scale. In contrast, female traders tend to operate on a smaller scale and primarily target local markets.[52] Hence, the expectation was that female traders, facing more significant resource limitations, are likely to prioritize cash assistance against conflict shocks, while male traders, with more substantial business operations, would probably advocate for preventive safety infrastructure measures to safeguard their enterprises given the higher stakes involved. However, our analysis reveals a contrary trend (Table 3.5). The average share of preferences among female traders for *Conflict cash relief* is observed to be 7 percentage points lower than that of male traders, all else being equal. Remarkably, female traders exhibit a higher share of preferences for *Improved market/warehouse safety infrastructure*. This pattern can possibly be contextualized within the

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[50] Traders' prior experiences with conflict and weather shocks were not included in the FML models due to the small number of observations with such experiences. However, we provide sub-group RPL model results in the latter part of this section.

[51] Based on the 2021 Nigerian maize trader dataset, comprising a total of 1,111 maize traders, the proportion of male traders in northern states is as follows: 91% in Kaduna, 97% in Kano, 100% in Katsina, and 70% in Plateau. Conversely, in the southern state, Oyo, male traders account for 41%.

[52] Our data suggest that 63% of male traders are large-scale traders, whereas only 24% of female traders belong to this category. Additionally, male traders tend to travel longer distances in their maize sourcing and selling activities. For instance, male traders operating in the northern regions typically engage with maize suppliers located about 132km away, while their female counterparts interact with suppliers located at a distance of around 45km.

broader understanding that women are often disproportionately vulnerable to the disruptive impacts of conflicts compared to their male counterparts (Isola and Tolulope, 2022).[53] Consequently, our findings suggest that female traders emphasize preventive safety infrastructure in the market or warehouse area, likely reflecting their vulnerability to conflict shocks. It may also suggest that conflict is one of the factors limiting women's engagement in maize trading in wholesale markets with prevalent conflicts, and such preventive policies might mitigate that constraint.

The heightened vulnerability of female traders potentially explains their higher share of preferences for *Improved market/warehouse security*. However, our analysis does not indicate a statistically significant difference in preferences for *Improved road security* between female and male traders, other factors constant. While security is key for female traders, security in the market may be more of a concern for them than security on the road, possibly due to the nature of their operations involving less extended travel. Similarly, female traders may place less emphasis on training in conflict risk alleviation strategies, such as diversifying suppliers or market channels, as their primary focus typically lies on local markets. Additionally, security concerns may deter female traders from conducting business activities during nighttime hours, potentially explaining the statistically insignificant preferences for *Improved market/warehouse area lighting*, which is typically essential during night operations.

Traders' gender also influences preferences for *Conflict insurance*, with female traders showing a 7 percentage point higher average share of preferences compared to their male counterparts, holding other factors constant. Empirical evidence from gendered studies on insurance demand or preferences shows mixed results. Some studies suggest that female actors

[53] Especially in Nigeria, women are disproportionally affected by conflicts, including violence incurred by Boko-Haram (Adelaja and George, 2019) and clashes between farmers and herders (Theophilus, 2020).

exhibit lower interest to insurance due to lower financial literacy or trust levels towards insurance institutions compared to male actors (for example, Akter et al., 2016). Others indicate that female actors have a stronger demand for insurance due to their increased vulnerability to risks and higher risk aversion (for instance, Sibiko, Veettil, and Qaim, 2018).[54] Our finding aligns more closely with the latter literature.

In terms of traders' business scale, other factors constant, large-scale traders exhibit a higher share of preferences for insurance than small-scale traders. This disparity may be explained by the credit constraints and high discount rates faced by small enterprises, making them less able to purchase insurance despite its potential benefits (Binswanger-Mkhize, 2012; Foster and Rosenzweig, 2010).[55] Instead, the results suggest that, all else being equal, small-scale traders prefer loans for investing in technologies that can mitigate losses from conflicts, as well as training in such strategies, compared to large-scale traders. Small traders' stronger preference for loans, relative to larger traders, may be partly attributed to their lower likelihood of receiving advance payments from their buyers, which could have been utilized instead of loans.[56] In addition, they may be more likely to require training in various risk-mitigating technologies or strategies compared to large traders, who are more likely to already possess them.

Traders' business scale is not a statistically significant determinant for preferences regarding cash relief or policies related to security services and hard infrastructure. It is observed from our data that travel distances to source or sell maize do not significantly vary across large and small trader groups, potentially explaining the lack of significant differences in their

[54] Akter et al. (2016) and Sibiko, Veettil, and Qaim (2018) explore gender disparities in weather-index insurance preferences among smallholder farmers in Bangladesh and Kenya, respectively.

[55] Binswanger-Mkhize (2012) also suggests that large, wealthier farmers who are sufficiently self-insured through their wealth, credit, or other risk management strategies have lower demand for insurance. However, our study focuses on Nigerian maize traders, small and medium-sized enterprises (Liverpool-Tasie and Parkhi, 2021), for whom this context may not be applicable.

[56] While 16% of large traders received advance payments from their buyers, only 8% of small traders did so.

preference for road security. Similarly, the proportion of traders who stored maize in their own warehouses versus in rented storage space was approximately 60% for both large and small traders, which could potentially account for the insignificant differences in their preferences for security, safety infrastructure, and lighting in the market or warehouse.

Education emerges as a significant factor influencing traders' preferences across various policy options. Traders with formal education may prefer insurance, investment in security facilitated by loans, and receiving training in risk-alleviating strategies as crucial components of addressing conflict shocks compared to those without formal education. This might be because educated traders may possess a deeper comprehension of the potential adverse effects of unforeseen conflicts. Another intriguing observation is that, holding other factors constant, educated traders express a stronger preference than less educated traders for measures that may not necessarily rely on government or public sector implementation, such as the provision of security measures or physical infrastructure. Educated individuals typically possess a better understanding of their political systems and exhibit lower levels of trust in political institutions (Lavallée, Razafindrakoto, and Roubaud, 2008; Seligson, 2002). Given that insurance and loans can also be provided by the market or private sector, we sought traders' opinions regarding the primary responsibility for, or leadership in, the provision of insurance and loans. On average, educated traders showed a lower level of support for the public sector compared to uneducated traders, with approximately a 10 percentage point difference (Appendix B, Table 3.10). A simple regression analysis confirms the negative correlation between traders' completion of formal education and their perception of the public sector's role in providing insurance and loans, indicating that educated traders are less likely to prefer the government as the primary entity responsible for such provisions (Appendix B, Table 3.11).

Similarly, educated traders' inclination towards market-oriented solutions is likely to be reflected in their higher share of preferences for improved lighting or electricity compared to that of uneducated traders, all else being constant. Despite the privatization of the electricity sector in Nigeria, with the private sector responsible for generating and distributing electricity, electricity access challenges persist due to underdeveloped supply infrastructure and an ineffective or weak regulatory framework (Arowolo and Perez, 2020). In this context, educated traders may advocate for public intervention to create an enabling environment for facilitating electricity access. Conversely, more educated traders show a relatively lower share of preferences for *Improved road security*, a domain unlikely to be addressed by the market but rather by the public sector.

Another interesting aspect regarding conflict shock policies involves the geographical location of traders' businesses, specifically whether they are based in the southern (Oyo) or northern (Kaduna, Kano, Katsina, and Plateau) regions of the country. The southern and northern regions differ not only in their geographical locations but also in their economic conditions. The northern region generally experiences higher poverty rates and more frequent conflicts, such as those associated with Boko Haram, which operates in the northeast region (Awojobi, 2014). However, despite the risks pertaining to the north, it is the southern traders who are more likely to experience conflict shocks as they depend on the north for sourcing maize (Vargas, Reardon, and Liverpool-Tasie, 2023). We find that traders in the southern region prioritize road security more highly in response to conflict shocks than their northern counterparts, all other factors held constant. This could possibly be attributed to the longer distances typically covered by southern traders to source maize from the northern maize-producing region.

Southern traders' higher share of preferences for improved lighting or electricity in the market and warehouse area may also be understood in the context of their reliance on the north for sourcing maize. Given the longer distances to the north and the potential exposure to conflict shocks during transit, sourcing activities could potentially become more burdensome for southern traders compared to their northern counterparts. Consequently, southern traders may purchase maize less frequently and need to store it over a longer period of time to meet their demand, incentivizing them to prioritize improved lighting and electricity in the warehouse.[57]

In contrast, northern traders have, on average, a stronger preference for *Conflict insurance* than southern traders, other factors constant. One might expect that southern traders, given their potentially heightened vulnerability to conflicts during transit, would prioritize preventive insurance more than their northern counterparts. However, we observe a relatively lower share of preferences for insurance among southern traders. Given that the shares of preferences across the nine conflict shock policy options sum to one, the aggregate of the average marginal effects for any single covariate (e.g., geographical location) equals zero (Allen IV, 2014). This suggests that preferences are substituted among the options, implying that the higher preferences of southern traders for very specific road security measures may lead to lower preferences for a more general risk protection scheme, such as insurance.[58] It could be that northern traders, situated in areas where conflict shocks are more frequent, prioritize insurance possibly as part of a broader risk management strategy.

While traders' years of trading experience may contribute to their overall resilience and ability to navigate risks, we do not find that it has a direct impact on their preferences for both

[57] Our data demonstrate that southern traders purchase maize for an average of 1.4 days in a typical week during the high trading season, whereas northern traders purchase more frequently, averaging 2.9 days. Furthermore, southern traders store maize for a longer duration (21 days) compared to northern traders (12 days), on average.

[58] The disparities between northern and southern traders may indeed primarily be attributed to southern traders' reliance on the north for sourcing maize and the subsequent longer travel distances. We attempted to additionally control for the actual distances (in kilometers) from traders' bases to their main sources in the north and discovered that the statistically significant average marginal effects for *Improved road security*, *Improved market/warehouse lighting*, and *Conflict insurance* became statistically insignificant.

conflict and weather shock policies (Tables 3.5 and 3.6). On the other hand, while traders' engagement in other income-generating jobs is not correlated with their preferences for conflict shock policies, it emerges as an influencing factor for weather shock policies (Table 3.6). Conflict shocks and weather shocks may have different implications and consequences for traders. For example, conflict shocks may directly disrupt transportation, market access, and traders' safety, hence making engagement in other income-generating activities less feasible or practical for traders. In contrast, weather shocks, such as floods or droughts, directly impact agricultural production and traders' trading businesses, making alternative income sources crucial for coping. We find that traders who have engaged in other jobs have a lower preference for loans than those without other jobs, all else being equal. Traders with multiple income streams are likely to have more resilient financial situations and less need for loans when facing weather shocks. They also have a relatively lower share of preferences for training, possibly because their other occupations may provide them with relevant knowledge and skills for coping with weather shocks. This may be particularly applicable to traders who engage in farming themselves, as they would likely have more varied experience with shocks and access to information from a broader network of farmers, which can directly assist their sourcing, compared to those solely involved in trading.

Concerning the other determinants of preferences for weather shock policies, traders' gender and region stand out as significant factors, affecting the share of preferences for all policy options except *Weather insurance*. Specifically, female traders exhibit a lower share of preferences than men, on average and other factors constant, for cash relief and a higher share of preferences for enhanced physical infrastructure in the market/warehouse area, similar to the findings for conflict shock policies. While women are often considered to be disproportionally affected by adverse weather shocks (Asfaw and Maggio, 2018), our data did not show differences in the exposure of female and male traders to weather shocks. Instead, the differences in policy preferences between male and female traders may be attributable to gender-specific perceptions of vulnerability to the effects of climate change. Anugwa, Agbo, and Agwu (2020) document that female farmers in Nigeria, who often face limited access and control over resources compared to their male counterparts, tend to perceive their vulnerability to be due primarily to inadequate access to physical resources such as irrigation facilities. In contrast, they note that male farmers tend to perceive their vulnerability primarily as stemming from a lack of weather forecasting technology such as radio access. This gendered perception aligns with our findings among traders. Male traders prioritize training in technologies as well as loans for investing in technologies to prevent weather-related losses more than female traders do. Conversely, female traders prioritize improved physical flood-proof infrastructure on roads and in the market/warehouse area as tangible and lasting solutions.[59]

Additionally, the relatively higher share of preferences among male traders for *Improved market/warehouse electricity*, compared to their female counterparts, may be attributable to their heavier electricity usage. Although less than 5% of both male and female traders paid electricity bills specific to their trading businesses (at stalls and warehouses), male traders spend an average of 4,450 Nigerian Naira per month, while female traders only spend 500 Naira. This heightened usage and expenditure on electricity may lead male traders to be more concerned about better electricity provisions.

There is also a discernible difference in policy preferences between traders in the south and those in the north. The northern region, particularly susceptible to droughts due to its dry

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[59] Road conditions can directly impact female traders' ability to transport maize safely, even if they are traveling shorter distances.

climatic conditions and facing the threat of annual floods (Kwari, Paul, and Shekarau, 2015), prioritizes enhanced hard infrastructure on roads and within the market/warehouse area to prevent the physical disruptions of weather shocks. However, these weather shocks occurring in the North are likely to affect southern traders in terms of maize prices as well as transportation and transaction costs, as they rely on the north for sourcing maize. This may explain why traders based in the south tend to prioritize soft infrastructure policy measures, such as cash relief to cover rising costs, along with loans and training to deal with weather shocks. In addition, southern traders' higher emphasis on market/warehouse electricity, similar to the findings in conflict shock cases, may be attributed to their longer storage durations, possibly due to the increased burden of sourcing induced by weather shocks.

The association between traders' business scale and their preference for weather shock policies shows a similar pattern to that observed in conflict shock policy preferences. Small-scale traders tend to prioritize loans and training, whereas large-scale traders, operating more substantial businesses, favor insurance as a formal protection scheme. In the context of weather shocks, large traders also display a stronger preference for improved road infrastructure compared to small traders. This inclination likely arises from the potentially higher transportation costs and associated risks faced by large traders, which may result from transporting larger volumes of maize over longer distances. Moreover, we find that small traders are more concerned about improved electricity access compared to large traders. Interestingly, small traders, on average, spend more on electricity bills (4,670 Naira) than large traders (2,920 Naira), despite both groups storing maize for the same average duration (15 days). One plausible explanation could be that small traders' stalls or warehouses are more likely to be located off-market or in rural areas, where access to electricity would be limited and expensive. Large traders may also have better warehouse facilities, which could lead to more efficient electricity usage. As a result, small traders may place greater importance on improved electricity access to support their business operations effectively.

In contrast to preferences for conflict shock policies, traders' education level is not statistically significantly associated with their preferences for weather shock policies. This distinction may stem from traders' focus on hard infrastructure policies, such as improved road and market/warehouse infrastructure, in response to weather shocks (Table 3.4). While soft infrastructure measures, which can potentially be provided by the private sector, were prioritized in response to conflict shocks (Table 3.3), hard infrastructure typically requires public investments and government-led initiatives. Recognizing these as more effective and crucial in responding to weather shocks, traders, including the educated, may prioritize government interventions over private sector solutions. As a result, education may not play a key role in shaping traders' preferences for weather shock policies.

Sup-group Analyses by Trader Groups

Given the diverse policy preferences influenced by traders' characteristics, we categorized our sample into various subgroups to further explore the heterogeneity in policy preferences across trader groups. These subgroups were defined based on traders' gender, business scale, educational background, and geographic region, similar to the FML analyses. Using the estimated parameters obtained from the subgroup-correlated RPL models, we computed the shares of preferences for each subgroup, as presented in Tables 3.7 and 3.8. Full correlated RPL results are provided in Appendix B, Tables 3.12 through 3.19. Additionally, we provide the results from the analysis based on traders' prior experience of conflict shocks in Appendix B, Table 3.20. However, conducting subgroup analyses for traders' prior experience of weather shocks and engagement in other jobs was not feasible due to the small number of observations of those who experienced weather shocks or were involved in other jobs.

The preferences for conflict shock policies among subgroups (Table 3.7) largely align with the overall policy preferences of the full sample. *Conflict cash relief* remains the most favored policy options for all subgroups except the southern trader group, who prioritize *Improved road security* (26.3% SOP) over cash relief (21.6% SOP). This prioritization is consistent with the findings from the FML model, as southern traders typically travel longer distances to source maize from the northern region. Traders in the north ranked cash relief as their most preferred policy option (34.9% SOP), followed by market/warehouse security (17% SOP) and road security (15.5% SOP), which are soft infrastructure measures that were prioritized by the overall traders in response to conflict shocks.

While female traders' most favored policy option is cash relief (26.1% SOP), their preference is more evenly distributed to market/warehouse security (23.7% SOP) and road security (20.5% SOP) compared to male traders, who place significant importance on cash relief (34.4% SOP) and much less on road security (17.6% SOP) and market/warehouse security (15.9% SOP). This divergence may stem from female traders being often more vulnerable to conflict shocks, leading them to prioritize preventive security measures and place relatively less importance on ex-post cash assistance.

Large and small-scale traders generally show a similar pattern towards the policy options, with the most discerning observation relating to the share of preferences for *Conflict insurance* (Table 3.7). While almost 7% of large traders are likely to identify insurance as their most preferred policy option, only 3.5% of small traders are likely to do so, reflecting the FML result that large traders have a higher share of preferences for insurance than small traders possibly due to their substantial business and higher stakes related to conflict shocks.

The subgroup analysis conducted among educated and uneducated traders reveals substantial disparities. Specifically, uneducated traders place a pronounced emphasis on cash relief (47.9% SOP), regarding it as more than three times as important as their second preferred option, road security (14.8% SOP). On the other hand, educated traders assign relatively less significance to cash relief (27.6% SOP). Their shares of preferences for alternative policy options, such as insurance, loans, and lighting – potentially market-oriented measures – are higher compared to those of their uneducated counterparts.

Additionally, Table 3.20 in Appendix B reports the estimated results by traders' past experience of conflict shocks. We find that both groups of traders, those who did and did not experience conflict shocks in the past, prioritize cash relief the most, followed by security measures on the road and in the market/warehouse area, albeit with slight differences. Traders who experienced conflict shocks previously tend to place relatively higher emphasis on road security (20.1% SOP) compared to market/warehouse security (12.0%), while those who did not experience conflicts in the past show more similar emphasis between road security (18.4% SOP) and market/warehouse security (17.3% SOP). This observation may suggest a potentially higher occurrence of conflicts on the road or that conflicts on the road may have more substantial impacts to traders compared to those occurring in the market/warehouse area.

Regarding weather shock policies (Table 3.8), the preferences of subgroups largely align with those of the full sample, favoring cash relief and hard infrastructure policy measures. While cash relief is the most preferred policy option overall, female traders deviate from this trend, predominantly favoring road infrastructure (36.2% SOP) over cash relief (24.3% SOP), whereas male traders exhibit a stronger preference for cash relief (33.7% SOP) over road infrastructure

(28.5% SOP). This discrepancy potentially underscores the prioritization of preventive measures (i.e., dams, culverts, or drainage) by female traders, contrasting with the focus on ex-post cash relief, which could provide immediate financial assistance but may not offer the same level of broader risk mitigation.

Moreover, small traders, uneducated traders, and southern traders tend to assign significantly higher priority to cash relief compared to large traders, educated traders, and northern traders, respectively. The latter groups place a comparable emphasis on both cash relief and enhanced road infrastructure. In addition, while both northern and southern traders prioritize cash relief, southern traders place relatively greater importance on road infrastructure (11.3% SOP) compared to market/warehouse infrastructure (4.7% SOP); in constrast, northern traders allocate relatively less priority to road infrastructure (29.6% SOP) compared to market/warehouse infrastructure (19.1% SOP). This highlights the potentially higher emphasis on safety measures during travel by southern traders, possibly attributable to the longer transit distances they must cover compared to their northern counterparts.

3.6 Conclusion and Policy Implications

This study explores the preferences of Nigerian maize wholesale traders regarding policies aimed at mitigating the impacts of weather and conflict shocks. Violent conflicts and extreme weather events significantly disrupt various stages of agrifood value chains, including production, harvest, storage, and transportation, thereby affecting maize traders' procurement, transportation, storage, and sales of maize. Given the crucial role of maize traders in bridging upstream producers and downstream consumers, the disruptions and challenges faced by maize traders not only affect their activities but also have broader implications for the entire maize value chain in Nigeria. However, despite the potential to enhance the resilience of maize value chains, there has been a notable neglect in efforts to understand the needs of maize traders and develop policies that effectively address their challenges.

By implementing a BWS experiment 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 policy options for addressing weather shocks, capturing maize traders' preferences for alternative policy options. The policy options for conflict shocks included financial measures (e.g., cash relief, insurance, and loans), as well as the provision of real-time safety information and training in technologies to minimize losses from conflicts. These, along with security services, were considered as soft infrastructure policy measures. Additionally, physical safety and electricity infrastructure were included as hard infrastructure policy measures. Weather shock policy options encompassed similar financial measures, alongside the provision of real-time weather information and training in technologies that can help prevent weather effects such as mold growth, all categorized as soft infrastructure policy measures. In addition, physical safety or flood-proof infrastructure, along with electricity infrastructure, were considered as hard infrastructure policy measures. The BWS approach allowed us to gain insights on how maize traders make trade-offs between these alternative policy options and understanding their most pressing needs.

Our results indicate that traders prioritize direct financial assistance (i.e., cash relief) when facing both conflict and weather shocks. However, our analysis also reveals distinct policy preferences among traders depending on the nature of the shocks. In the context of conflict shocks, which are caused by human activities, traders tend to prioritize soft infrastructure policy measures, such as enhanced security services on roads and within market/warehouse areas. This prioritization may reflect their need to address the security challenges inherent during violent conflicts. Conversely, when confronted with weather shocks, the priority shifts to hard infrastructure policy measures, such as physical flood-proof infrastructure on roads and within market/warehouse areas. This shift is likely influenced by the physical and logistical challenges posed by natural events and potentially underscores the adaptability of traders' policy preferences to the specific challenges they face.

We have also found that policy preferences vary across trader subgroups categorized by their gender, business scale, education, involvement in other income-generating jobs, and geographic region of operation. Interestingly, contrary to the expectation that male traders, often having greater resources and more extensive businesses than female traders, would prioritize preventive hard infrastructure against shocks to protect their substantial businesses, we observe that male traders predominantly prefer ex-post cash relief in response to both conflict and weather shocks. Instead, it is the female traders who prioritize physical infrastructure following conflict and weather shocks, likely due to their heightened vulnerability to these shocks. Particularly for weather shocks, the female trader group was the only subgroup that prioritized enhanced road infrastructure over cash relief. Another significant determinant for policy preferences is traders' geographical region. We consistently find that traders in the southern region more highly prioritize road security in response to conflict shocks than their northern counterparts, likely due to the longer distances typically covered by southern traders to source maize from the northern maize-producing region.

While some policy measures necessitate public investment and government-led initiatives, such as enhancing physical infrastructure or security services, there are also areas where government policies can foster a viable environment for the private sector to contribute. In particular, we find that educated traders express a preference for measures that can be provided by the market or private sector, such as insurance and loans, which may not necessarily be provided by the government. Additionally, given the privatization of Nigeria's energy sector, improved access to electricity may largely depend on the private sector as well. There is an opportunity for the government to create an enabling environment for private sector participation in these areas to effectively address the shocks.

The heterogeneity in preferences, influenced by trader characteristics and the nature of shocks, emphasizes the necessity for tailored, context-specific policy interventions to effectively address the multifaceted challenges encountered by maize traders, who serve as a vital link in the maize value chain. In this study, we were unable to account for traders' prior experiences with weather shocks due to the limited number of observations, which likely influences their perception on these shocks and policy preferences. Moreover, traders' involvement in other income generating activities is also likely to shape their policy preferences, as they may bring forth knowledge or experiences from those activities, particularly if involved in farming. However, these factors could not be incorporated in this study. Nevertheless, amidst growing concerns about the impact of various shocks on local and global agrifood value chains, this study lays the foundation for future research into a wide range of policy preferences and effective policy development to tackle the complex challenges.

REFERENCES

Adebayo, A.A., and O. Akanle. 2014. "Gender and the academy in Nigeria." *African Journal for the Psychological Studies of Social Issues* 17((2014): 147-154.

Adelaja, A. and J. George. 2019. "Effects of conflict on agriculture: Evidence from the Boko Haram insurgency." *World Development* 117:184-195.

Ajadi, A.A., O.I. Oladele, K. Ikegami, and T. Tsuruta. 2015. "Rural women's farmers access to productive resources: the moderating effect of culture among Nupe and Yoruba in Nigeria." *Agriculture & Food Security* 4:1-9.

Akter, S., T.J. Krupnik, F. Rossi, and F. Khanam. 2016. "The influence of gender and product design on farmers' preferences for weather-indexed crop insurance." *Global Environmental Change* 38:217-229.

Allen IV, J.E. 2014. "Determinants of land allocation in a multi-crop farming system: an application of the fractional multinomial logit model to agricultural households in Mali." Working paper No. 329-2016-13343, Department of Agricultural Economics, University of Kentucky.

Anugwa, I.Q., P.C. Agbo, and A.E. Agwu. 2020. "Gender Differences in Perceived Vulnerability and Adaptation Strategies to Climate Change Effects on Arable Crop Production in Enugu State, Nigeria." *Handbook of Climate Change Management: Research, Leadership, Transformation*, pp. 1-20.

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.

Arowolo, W. and Y. Perez. 2020. "Market reform in the Nigeria power sector: A review of the issues and potential solutions." *Energy policy* 144:111580.

Asfaw, S. and G. Maggio. 2018. "Gender, weather shocks and welfare: Evidence from Malawi." *The Journal of Development Studies* 54(2):271-291.

Awojobi, O.N. 2014. "The socio-economic implications of Boko Haram insurgency in the north-east of Nigeria." *International Journal of Innovation and scientific research* 11(1):144-150.

Barrett, C., T. Reardon, J. Swinnen, and D. Zilberman. 2019. "Structural transformation and economic development: insights from the agri-food value chain revolution." *Cornell University*.

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.

Binswanger-Mkhize, H.P. 2012. "Is there too much hype about index-based agricultural insurance?" *Journal of Development studies* 48(2):187-200.

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.

Ellis, F. 2012. "'We Are All Poor Here': economic difference, social divisiveness and targeting cash transfers in Sub-Saharan Africa." *Journal of Development Studies* 48(2):201-214.

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.

Foster, A.D., and M.R. Rosenzweig. 2010. "Is there surplus labor in rural India?" Economic Growth Center Discussion Paper 991, New Haven, CT: Yale University.

Ghosal, S. 2013. "Soft or hard: infrastructure matters in rural economic empowerment." *Journal of Infrastructure Development* 5(2):137-149.

Hess, S., and K. Train. 2017. "Correlation and scale in mixed logit models." *Journal of choice modelling* 23:1-8.

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

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." *The World Bank 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.

Kuhfeld, W.F. 2005. “Experimental design, efficiency, coding, and choice designs.” *Marketing research methods in SAS: Experimental design, choice, conjoint, and graphical techniques* 47-97.

Kwari, J.W., M.K. Paul, and L.B. Shekarau. 2015. “The impacts of flooding on socio-economic development and agriculture in Northern Nigeria: A case study of 2012 flooding in Yola and Numan Areas of Adamawa State Nigeria.” *International Journal of Scientific & Engineering Research* 6(7):1433-1442.

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

Lavallée, E., M. Razafindrakoto, and F. Roubaud. 2008. “Corruption and trust in political institutions in sub-Saharan Africa.” *CSAE Conference 2008 - Economic Development in Africa*, p.21. Oxford, United Kingdom.

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., T.S. Jayne, and R. Mofya-Mukuka. 2013. “Zambia’s input subsidy programs.” *Agricultural Economics* 44:613-628.

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.

Mullahy, J. 2015. "Multivariate fractional regression estimation of econometric share models." *Journal of econometric methods* 4(1):71-100.

Muoghalu, C.O. and C.A. Abrifor. 2012. "Urban poor women and governance in Nigeria." *European Scientific Journal* 8(5):176-185.

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.

Reardon, T., K. Chen, B. Minten, and L. Adriano. 2012. *The quiet revolution in staple food value chains: Enter the dragon, the elephant, and the tiger*. Asian Development Bank.

Rocker, S.J. 2019. "Value Chain Coordination: A New Strategy for Developing Soft Infrastructure in Regional Agri-Food Systems in the United States." PhD dissertation, The Pennsylvania State University.

Seligson, M. 2002. "The Impact of Corruption on Regime Legitimacy: A Comparative Study of Four Latin American Countries" *Journal of Politics* 64(2): 408-433.

Sibiko, K.W., P.C. Veettil, and M. Qaim. 2018. "Small farmers' preferences for weather index insurance: insights from Kenya." *Agriculture & Food Security* 7:1-14.

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.

Tadesse, G. and O. Badiane. 2020. "Policy responses to rapidly transforming midstream value chain segments in Africa: The case of the millet sector in Senegal." In D. Resnick, X. Diao, and G. Tadesse, ed. *2020 Annual trends and outlook report: Sustaining Africa's agrifood system transformation: The role of public policies*. Washington, DC, and Kigali: International Food Policy Research Institute (IFPRI) and AKADEMIYA2063, Chapter 7, pp. 71-86.

Theophilus, A.T. 2020. "The dynamics of farmers and herdsmen violent conflicts in Nigeria: A reflection on the vulnerability of women and children." *Covenant Journal of Politics and International Affairs* 8(2):1-20.

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

Uduji, J.I., and E.N. Okolo-Obasi. 2018. "Young rural women's participation in the e-wallet programme and usage intensity of modern agricultural inputs in Nigeria." *Gender, Technology and Development* 22(1):59-81.

Umar, N. and A. Gray. 2023. "Flooding in Nigeria: a review of its occurrence and impacts and approaches to modelling flood data." *International Journal of Environmental Studies* 80(3):540-561.

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.

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

——. 2022. *Grain: World Markets and Trade.* Foreign Agricultural Service, USDA.

Vos, R. and A. Cattaneo. 2020. "Smallholders and rural people: making food system value chains inclusive." *2020 Global Food Policy Report: Building Inclusive Food Systems*. International Food Policy Research Institute, Chapter 2, pp. 14-26.

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 A. TABLES AND FIGURES

Table 3.1 Risk management instruments and policy options

Risk management instrument	Policy type	Policy options for conflict shocks *(Short name)*	Policy options for weather shocks *(Short name)*
Financial instruments	Soft – Financial service	Conflict cash relief *("Conflict cash relief")*	Weather cash relief *("Weather cash relief")*
		Conflict insurance *("Conflict insurance")*	Weather insurance *("Weather insurance")*
		Loans for investment in technology to prevent conflict losses (e.g., security camera) *("Loans for security")*	Loans for investment in technology to prevent weather losses (e.g., better storage facility) *("Loans for weather tech")*
Enterprise management practices	Soft – Information technology	Call center for real-time information on the safety of routes *("Real-time safety info")*	Call center for real-time information on flooded roads and alternative routes *("Real-time weather info")*
Technology development and adoption		Training in technologies to minimize conflict losses (e.g., strategies to diversify suppliers) *("Conflict training")*	Training in technologies to deal with weather effects (e.g., mold growth prevention) *("Weather training")*
Public policy and programs	Soft – Security service	More functional security on the roads *("Improved road security")*	-
		More functional security in the market/warehouse area *("Improved market/warehouse security")*	-
Infrastructure investment	Hard – Road infrastructure	-	More functional dams, culverts, or drainage on the roads *("Improved road infra")*
	Hard – Market/ warehouse safety infrastructure	More functional safety concrete barriers in the market/warehouse area *("Improved market/warehouse safety infra")*	More functional flood barriers, sandbags, or tarps in the market/warehouse area *("Improved market/warehouse flood-proof infra")*
	Hard – Energy	More functional electricity in the market/warehouse area (e.g., for reliable lighting) *("Improved market/warehouse lighting")*	More functional electricity in the market/warehouse area (e.g., for temperature-controlled warehouses) *("Improved market/warehouse electricity")*

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.

Figure 3.1 Examples of BWS choice sets for conflict and weather shock policies

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**

Table 3.2 Summary statistics of maize traders' characteristics

Variable	Definition	Obs.	Mean	Std. Dev.
Maize trading	1 = Engaging in maize trading business as of May–Aug. 2023	300	0.97	0.17
Age	Age in years	291	47.36	10.27
Female	1 = Female, 0 = Male	291	0.20	0.40
Formally educated	1 = Completed formal education (primary, secondary, or post-secondary)	291	0.65	0.48
Large-scale	1 = Large (monthly sales $\geq$ 32 tons between Aug. 2020 and Feb. 2021), 0 = Small (monthly sales < 32 tons between Aug. 2020 and Feb. 2021)	291	0.55	0.50
Engaged in other job	1 = Engaged in other income-generating jobs between Aug. 2020 and Jul. 2021	300	0.11	0.31
South	1 = South, 0 = North	300	0.20	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

Table 3.3 Correlated RPL model results for conflict shock policies

	Conflict shock policies	Mean	Std. Dev.	Share of preferences (%)
Soft	*Conflict cash relief*	2.501***	0.753***	34.5
		(0.082)	(0.076)	(0.014)
	Real-time safety info – ***BASE***	0.000	-	2.8
				(0.002)
	Conflict training	0.336***	0.489***	4.0
		(0.065)	(0.060)	(0.002)
	Improved road security	1.828***	0.861***	17.6
		(0.073)	(0.067)	(0.008)
	Conflict insurance	0.474***	1.264***	4.6
		(0.071)	(0.075)	(0.003)
	Loans for security	0.254***	0.897***	3.7
		(0.071)	(0.069)	(0.002)
	Improved market/warehouse security	1.777***	0.640***	16.8
		(0.072)	(0.066)	(0.008)
Hard	*Improved market/warehouse safety infra*	1.310***	0.516***	10.5
		(0.071)	(0.064)	(0.005)
	Improved market/warehouse lighting	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.

Table 3.4 Correlated RPL model results for weather shock policies

	Weather shock policies	Mean	Std. Dev.	Share of preferences (%)
Soft	*Weather cash relief*	2.277***	0.711***	35.4
		(0.080)	(0.090)	(0.014)
	Loans for weather tech	0.340***	0.762***	5.1
		(0.065)	(0.079)	(0.003)
	Weather insurance	0.217***	1.263***	4.5
		(0.068)	(0.081)	(0.003)
	*Real-time weather info – **BASE***	0.000	-	3.6
				(0.002)
	Weather training	0.140**	0.493***	4.2
		(0.065)	(0.069)	(0.003)
Hard	*Improved road infra*	1.999***	1.592***	26.8
		(0.076)	(0.069)	(0.011)
	Improved market/warehouse flood-proof infra	1.482***	1.263***	16.0
		(0.072)	(0.065)	(0.007)
	Improved market/warehouse electricity	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.

Table 3.5 Average marginal effects for the SOPs of conflict shock policies (FML)

	Soft infrastructure						Hard infrastructure	
VARIABLES	(1) *Conflict cash relief*	(2) *Conflict Insurance*	(3) *Loans for security*	(4) *Conflict training*	(5) *Improved road security*	(6) *Improved market/ warehouse security*	(7) *Improved market/ warehouse safety infra*	(8) *Improved market/ warehouse lighting*
1 = Female	-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 = South	0.0008	-0.041***	-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. Base policy is *Real-time safety info*. The FML model converged with a log pseudolikelihood of -535.164 and a Wald chi-squared value of 127.98 (Prob > chi-squared = 0.000).

Table 3.6 Average marginal effects for the SOPs of weather shock policies (FML)

	Soft infrastructure				Hard infrastructure		
VARIABLES	(1) *Weather cash relief*	(2) *Weather insurance*	(3) *Loans for weather tech*	(4) *Weather training*	(5) *Improved road infrastructure*	(6) *Improved market/warehouse flood-proof infra*	(7) *Improved market/warehouse electricity*
1 = Female	-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 = South	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. Base policy is *Real-time weather info*. The FML model converged with a log pseudolikelihood of -495.514 and a Wald chi-squared value of 104.60 (Prob > chi-squared = 0.000).

Table 3.7 SOPs by sub-groups for conflict shock policies (Correlated RPL)

	Conflict shock policies	Share of preferences (%)							
		Gender		Scale		Formal education		Region	
		Female	Male	Large	Small	Educated	Un-educated	North	South
Soft	*Conflict 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)
	*Real-time safety info – **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)
	Conflict 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)
	Improved 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)
	Conflict 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)
	Loans for security	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)
	Improved 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)
Hard	*Improved market/ warehouse safety infra*	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)
	Improved market/ warehouse lighting	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)
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.

Table 3.8 SOPs by sub-groups for weather shock policies (Correlated RPL)

	Weather shock policies	Share of preferences (%)							
		Gender		Scale		Formal education		Region	
		Female	Male	Large	Small	Educated	Uneducated	North	South
Soft	*Weather 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 for weather tech	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)
	Weather 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)
	*Real-time weather info – **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)
	Weather 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	*Improved road infra*	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)
	Improved market/warehouse flood-proof infra	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)
	Improved market/warehouse electricity	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.

APPENDIX B. SUPPLEMENTARY MATERIALS

Table 3.9 Best-worst scores of conflict and weather shock policies

		Best counts (B)	Worst counts (W)	BW score (B-W)
Conflict shock policies				
Soft	*Conflict cash relief*	752	66	686
	Real-time safety info	58	590	-532
	Conflict training	108	329	-221
	Improved road security	530	106	424
	Conflict insurance	196	442	-246
	Loans for security	121	548	-427
	Improved market/warehouse security	456	90	366
Hard	*Improved market/warehouse safety infra*	337	168	169
	Improved market/warehouse lighting	142	361	-219
	Number of choices made (9 choice sets for 300 traders)	2,700	2,700	
Weather shock policies				
Soft	*Weather cash relief*	688	88	600
	Loans for weather tech	228	362	-134
	Weather insurance	209	447	-238
	Real-time weather info	89	466	-377
	Weather training	88	374	-286
Hard	*Improved road infra*	599	111	488
	Improved market/warehouse flood-proof infra	392	130	262
	Improved market/warehouse electricity	107	422	-315
	Number of choices made (8 choice sets for 300 traders)	2,400	2,400	

Table 3.10 Proportion of traders supporting public provision of insurance and loans

	Formal education					
	Educated			Uneducated		
Public provision of:	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Insurance in response to conflict shocks	189	.87	.34	101	.98	.14
Insurance in response to weather shocks	189	.88	.32	101	.99	.10
Loans in response to conflict shocks	189	.79	.41	101	.89	.31
Loans in response to weather shocks	189	.77	.42	101	.84	.37

Table 3.11 Perception on public implementation of insurance and loans

VARIABLES	(1) *Conflict insurance*	(2) *Weather insurance*	(3) *Loans for security*	(4) *Loans for weather tech*
1 = Female	0.0509	0.0770	-0.0336	-0.102
	(0.0515)	(0.0476)	(0.0671)	(0.0718)
1 = Large-scale	-0.0307	-0.0453	-0.0951**	-0.101**
	(0.0367)	(0.0339)	(0.0478)	(0.0511)
1 = Formally educated	-0.117***	-0.114***	-0.0838*	-0.0638
	(0.0379)	(0.0350)	(0.0494)	(0.0529)
1 = Engaged in other job	-0.0266	-0.0104	-0.0665	-0.0506
	(0.0563)	(0.0520)	(0.0734)	(0.0785)
1 = South	-0.0152	-0.0259	-0.0234	0.0397
	(0.0522)	(0.0483)	(0.0681)	(0.0729)
Years of trading	0.000993	0.000580	0.00221	0.000455
	(0.00197)	(0.00182)	(0.00256)	(0.00274)
Constant	0.972***	0.996***	0.900***	0.898***
	(0.0606)	(0.0560)	(0.0791)	(0.0846)
Observations	285	285	285	285
R-squared	0.046	0.058	0.038	0.030

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS regression was employed, with the dependent variables being a binary variable taking the value of 1 if the trader indicated that the government (at the local, state, or federal level) should be primarily responsible for providing insurance or loans, and 0 if they indicated that the private sector (wholesaler associations, formal financial institutions, credit-saving associations, or non-governmental organizations) should lead the effort.

Table 3.12 Correlated RPL results for conflict shock policies by gender

		Female traders			Male traders		
	Conflict shock policies	Mean	Std. Dev.	SOPs	Mean	Std. Dev.	SOPs
Soft	*Conflict 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)
	*Real-time safety info – **BASE***	0.000	-	2.2	0.000	-	2.8
				(0.003)			(0.002)
	Conflict 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)
	Improved 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)
	Conflict 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 for security	-0.047	0.517***	2.1	0.437***	0.963***	4.3
		(0.176)	(0.177)	(0.003)	(0.081)	(0.067)	(0.003)
	Improved 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	*Improved market/ warehouse safety infra*	1.467***	1.575***	9.5	1.385***	0.676***	11.1
		(0.182)	(0.232)	(0.011)	(0.081)	(0.078)	(0.006)
	Improved market/ warehouse lighting	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.

Table 3.13 Correlated RPL results for weather shock policies by gender

		Female traders			Male traders		
	Weather shock policies	Mean	Std. Dev.	SOPs	Mean	Std. Dev.	SOPs
Soft	*Weather 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 for weather tech	0.192	1.600***	4.7	0.438***	0.637***	5.4
		(0.155)	(0.175)	(0.006)	(0.074)	(0.078)	(0.003)
	Weather 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)
	*Real-time weather info – **BASE***	0.000	-	3.9	0.000	-	3.5
				(0.005)			(0.002)
	Weather 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	*Improved road infra*	2.223***	1.987***	36.2	2.102***	1.299***	28.5
		(0.196)	(0.158)	(0.034)	(0.090)	(0.074)	(0.014)
	Improved market/ warehouse flood-proof infra	1.420***	0.914***	16.2	1.614***	1.062***	17.5
		(0.166)	(0.128)	(0.017)	(0.085)	(0.068)	(0.010)
	Improved market/ warehouse electricity	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.

Table 3.14 Correlated RPL results for conflict shock policies by scale

		Large traders			Small traders		
	Conflict shock policies	Mean	Std. Dev.	SOPs	Mean	Std. Dev.	SOPs
Soft	*Conflict 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)
	*Real-time safety info – **BASE***	0.000	-	2.5	0.000	-	2.8
				(0.002)			(0.003)
	Conflict 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)
	Improved 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)
	Conflict 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 for security	0.586***	0.938***	4.6	0.135	0.739***	3.2
		(0.102)	(0.075)	(0.004)	(0.107)	(0.079)	(0.003)
	Improved 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	*Improved market/ warehouse safety infra*	1.632***	0.671***	12.9	1.220***	0.736***	9.5
		(0.104)	(0.095)	(0.008)	(0.107)	(0.106)	(0.007)
	Improved market/ warehouse lighting	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.

Table 3.15 Correlated RPL results for weather shock policies by scale

		Large traders			Small traders		
	Weather shock policies	Mean	Std. Dev.	SOPs	Mean	Std. Dev.	SOPs
Soft	*Weather 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 for weather tech	0.278***	0.627***	4.4	0.330***	0.837***	6.3
		(0.089)	(0.102)	(0.004)	(0.097)	(0.097)	(0.005)
	Weather 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)
	*Real-time weather info – **BASE***	0.000	-	3.3	0.000	-	4.5
				(0.003)			(0.004)
	Weather 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	*Improved road infra*	2.201***	1.558***	29.8	1.668***	1.456***	24.1
		(0.108)	(0.105)	(0.017)	(0.111)	(0.087)	(0.016)
	Improved market/ warehouse flood-proof infra	1.623***	1.220***	16.7	1.152***	0.983***	14.4
		(0.102)	(0.100)	(0.011)	(0.103)	(0.082)	(0.010)
	Improved market/ warehouse electricity	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.

Table 3.16 Correlated RPL results for conflict shock policies by region

		Northern traders			Southern traders		
	Conflict shock policies	Mean	Std. Dev.	SOPs	Mean	Std. Dev.	SOPs
Soft	*Conflict 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)
	*Real-time safety info – **BASE***	0.000	-	2.7	0.000	-	2.8
				(0.002)			(0.004)
	Conflict 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)
	Improved 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)
	Conflict 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 for security	0.393***	0.842***	3.9	-0.271	1.194***	2.1
		(0.079)	(0.058)	(0.003)	(0.185)	(0.163)	(0.003)
	Improved 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	*Improved market/ warehouse safety infra*	1.610***	0.659***	13.3	0.295*	0.106	3.7
		(0.082)	(0.079)	(0.007)	(0.176)	(0.170)	(0.005)
	Improved market /warehouse lighting	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.

Table 3.17 Correlated RPL results for weather shock policies by region

		Northern traders			Southern traders		
	Weather shock policies	Mean	Std. Dev.	SOPs	Mean	Std. Dev.	SOPs
Soft	*Weather 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 for weather tech	0.296***	0.869***	4.3	0.043	0.694***	2.2
		(0.075)	(0.081)	(0.003)	(0.153)	(0.163)	(0.005)
	Weather 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)
	*Real-time weather info – **BASE***	0.000	-	3.2	0.000	-	2.1
				(0.002)			(0.005)
	Weather 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	*Improved road infra*	2.235***	1.256***	29.6	1.700***	1.611***	11.3
		(0.090)	(0.076)	(0.013)	(0.181)	(0.144)	(0.021)
	Improved market/ warehouse flood-proof infra	1.797***	0.910***	19.1	0.828***	1.353***	4.7
		(0.086)	(0.074)	(0.010)	(0.164)	(0.132)	(0.010)
	Improved market/ warehouse electricity	-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.

Table 3.18 Correlated RPL results for conflict shock policies by formal education

		Educated traders			Uneducated traders		
	Conflict shock policies	Mean	Std. Dev.	SOPs	Mean	Std. Dev.	SOPs
Soft	*Conflict 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)
	*Real-time safety info – **BASE***	0.000	-	3.5	0.000	-	1.7
				(0.002)			(0.002)
	Conflict 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)
	Improved 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)
	Conflict 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 for security	0.285***	0.768***	4.7	0.752***	1.708***	3.6
		(0.087)	(0.062)	(0.003)	(0.138)	(0.104)	(0.004)
	Improved 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	*Improved market/ warehouse safety infra*	1.127***	0.668***	10.9	1.842***	0.560***	10.8
		(0.087)	(0.078)	(0.006)	(0.134)	(0.132)	(0.011)
	Improved market/ warehouse lighting	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.

Table 3.19 Correlated RPL results for weather shock policies by formal education

		Educated traders			Uneducated traders		
	Weather shock policies	Mean	Std. Dev.	SOPs	Mean	Std. Dev.	SOPs
Soft	*Weather 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 for weather tech	0.617***	1.112***	8.2	0.006	1.078***	2.7
		(0.085)	(0.084)	(0.005)	(0.122)	(0.118)	(0.003)
	Weather 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)
	*Real-time weather info - **BASE***	0.000	-	4.4	0.000	-	2.6
				(0.003)			(0.003)
	Weather 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	*Improved road infra*	1.814***	1.142***	27.1	2.187***	1.176***	23.6
		(0.093)	(0.074)	(0.014)	(0.144)	(0.103)	(0.020)
	Improved market/ warehouse flood-proof infra	1.245***	0.868***	15.4	1.796***	0.939***	15.9
		(0.087)	(0.070)	(0.009)	(0.137)	(0.099)	(0.015)
	Improved market/ warehouse electricity	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.

Table 3.20 Correlated RPL results for conflict shock policies by experience of conflict shocks

		Experienced			Did not experience		
	Conflict shock policies	Mean	Std. Dev.	SOPs	Mean	Std. Dev.	SOPs
Soft	*Conflict cash relief*	2.638***	0.419*	35.5	2.311***	0.131	27.5
		(0.221)	(0.230)	(0.184)	(0.085)	(0.093)	(0.048)
	*Real-time safety info – **BASE***	0.000	-	2.2	0.000	-	2.7
				(0.012)			(0.005)
	Conflict training	0.703***	0.633***	3.9	0.338***	0.436***	3.9
		(0.184)	(0.144)	(0.017)	(0.074)	(0.071)	(0.018)
	Improved road security	2.194***	1.911***	20.1	1.669***	0.772***	18.4
		(0.213)	(0.156)	(0.173)	(0.080)	(0.071)	(0.081)
	Conflict Insurance	0.069	2.179***	7.3	0.553***	1.865***	8.8
		(0.234)	(0.199)	(0.097)	(0.085)	(0.092)	(0.141)
	Loans for security	0.868***	1.102***	6.3	0.348***	1.005***	4.7
		(0.201)	(0.157)	(0.105)	(0.080)	(0.069)	(0.061)
	Improved market/ warehouse security	1.724***	1.418***	12.0	1.694***	0.582***	17.3
		(0.207)	(0.155)	(0.081)	(0.081)	(0.081)	(0.050)
Hard	*Improved market/ warehouse safety infra*	1.234***	0.365**	6.8	1.283***	0.529***	11.0
		(0.195)	(0.165)	(0.040)	(0.078)	(0.082)	(0.038)
	Improved market/ warehouse lighting	0.820***	1.699***	6.0	0.643***	0.494***	5.8
		(0.199)	(0.161)	(0.074)	(0.078)	(0.080)	(0.025)
	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.