Technology Adoption and Economic Transformation in Kenya

The Role of Information, Risk, and Informal Markets



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Propositions

1. Game-based learning and gamification are a panacea for the challenges in agricultural extension in low-income countries (this thesis).
2. Market incentives alone are insufficient to ensure high food quality standards in informal markets in low-income countries in the absence of third-party verification (this thesis).
3. The agricultural research agenda for low-income countries is often shaped by lobbyists and politicians, many of whom are neither researchers nor scientists.
4. Sub-Saharan Africa will never catch up with the rest of the world in addressing poverty and food insecurity with the current "breed" of politicians in the region.
5. Success as a scholar post-PhD is a function of where you published, the university you attended, and the networks you built—individual brilliance is in the error term.
6. Social and economic inclusion are theoretical ideals that are rarely realized in practice.

Propositions belonging to the thesis, entitled

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To my family, the first small-scale farm household I learnt from.

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Chapter 1

Introduction

1.1. Overview

Agricultural productivity growth is fundamental to economic development for low-income countries (de Janvry & Sadoulet, 2020). Some parts of the world experienced significant gains in agricultural productivity during the Green Revolution (Gollin et al., 2021). Economic development in these areas has since been marked by a declining share of agriculture in gross domestic product (GDP), a reduction in agricultural employment, and a decrease in the number of small-scale farmers growing cereals primarily for subsistence (Suri & Udry, 2022). While most regions have progressed along this path, Sub-Saharan Africa (SSA) continues to lag behind (Suri & Udry, 2022; Wollburg et al., 2024). Small scale farmers account for 80% of agricultural producers in the region (Lowder et al., 2016), and the low adoption of productivity enhancing technologies by the farmers despite their availability is considered a key driver of the stagnant agricultural productivity (Bridle et al., 2020; Macours, 2019; Magruder, 2018; Takahashi et al., 2020).

Learning about the impact of agricultural technologies and their adoption by small scale farmers is often slow and complex due to the time lag between adoption and observable outcomes, especially when results depend on uncertain factors like weather conditions (Bold et al., 2017). Furthermore, the drivers of adoption often extend beyond the farm, underscoring the need for a multidimensional understanding of adoption constraints and process. Literature highlights three main paradigms to explain technology adoption in SSA: the innovation-diffusion paradigm emphasizes information as the key driver of adoption; the economic constraints paradigm frames adoption as a utility-maximizing decision shaped by resource availability; and the adopter-

perception paradigm focuses on the role of farmers' perceptions of their needs and the attributes of new technologies on choices (Ruzzante et al., 2021). Across these paradigms, the common barriers to adoption are liquidity constraints (Karlan et al., 2014), information (Anderson & Feder, 2007; Takahashi et al., 2020), risk and uncertainty (Boucher et al., 2024; Emerick et al., 2016; Karlan et al., 2014), and market inefficiencies (Porteous, 2020).

This thesis focuses on three themes, namely the role of agricultural risk, information, and informal markets in technology adoption by small-scale farmers in SSA with the aim of generating more insights on the productivity and adoption gaps. On agricultural risk and uncertainty, this thesis critiques the prevailing focus on production-related risks and advocates for a broader conceptualization that captures the multiple, overlapping risks farmers face (Komarek et al., 2020). It also examines how farmers' preferences for technology are influenced by specific technology attributes as in the adopter-perception paradigm (Macours, 2019), and the role of behavioral factors. When preferences are unknown like in the case of new innovations, economists use various approaches such as contingent valuation to assess preferences and demand ex-ante to inform the design of the innovations, and policy (Johnston et al., 2017). However, farmer preferences may shift when presented with new information about a technology, or alternative technologies. This thesis contributes to understanding how such unstable preferences might contribute to the persistent gap in technology adoption.

Regarding information, this thesis evaluates the effectiveness of innovative extension methods as alternatives to traditional narrative-based approaches. According to the innovation-diffusion paradigm, the expectation is that providing small scale farmers with information about productivity enhancing technologies and how to use them would result in increased uptake (Anderson & Feder, 2004, 2007; Cook et al., 2021). Several evaluations have examined the impact

of information interventions on adoption but the findings in the literature remain inconclusive (Takahashi et al., 2020). Comparative studies assessing the effectiveness of various extension approaches relative to the conventional extension are limited.

On informal markets, this thesis addresses one of the most critical challenges namely incomplete information, especially when it comes to unobservable product attributes such as quality (Aker, 2010; Bai, 2025). Because consumers cannot easily and accurately verify product quality, traders often do not receive a premium for higher-quality produce. As a result, lower-quality products dominate the market, since traders lack incentives to invest in quality (Akerlof, 1970). This has serious public health implications when it comes to food safety. The thesis investigates whether providing "easily accessible" information on quality can influence both the supply of and demand for safe, high-quality food in contexts where formal regulation and certification systems are weak or absent, as is typical of informal markets.

In this regard, the thesis contributes directly to the growing literature on the use of market mechanisms and incentives to improve food quality (Jaffee et al., 2019; Unnevehr, 2022), and indirectly to the literature on agricultural technology adoption (Hoffmann et al., 2021; Magnan et al., 2021). A growing body of evidence shows that changes in how agricultural output markets function can significantly influence farmers' incentives to invest in quality upgrading along different value chains. For instance, in Senegal, anticipated market reforms, specifically the introduction of weighing scales and quality labels, led onion farmers to increase investment in quality-enhancing inputs (Bernard et al., 2017). Similarly, Treurniet (2021) found that the introduction of individual quality-based incentives improved the quality of milk supplied by dairy farmers in Indonesia.

Although the thesis is organized into five standalone chapters, the research questions addressed are closely interconnected as follows: at the center of economic transformation is the uptake of agricultural innovations and technologies that either enhance productivity or enable effective management of agricultural risks. A farmer's decision to adopt a technology depends on her willingness to pay for desirable attributes, shaped by perceptions of both the technology and the risks she faces. Information plays a pivotal role, particularly for new technologies, by influencing awareness and understanding of the application and use of innovations at both farm and market levels. Finally, well-functioning markets where (unobservable) quality is rewarded and premiums are effectively transmitted to farmers can create strong incentives for the adoption of quality-enhancing technologies, thereby improving product quality in the markets, implying access to markets and high farm incomes. While the empirical analysis focuses on Kenya, the insights generated are broadly relevant and applicable across SSA.

The following sections present in detail the thesis's three core themes—agricultural risk, agricultural extension, and informal markets and food safety in SSA—followed by a brief overview of the overall objective and research questions, methods used and a roadmap of the thesis.

1.2. Agricultural risk and technology adoption in SSA

Farming is inherently risky, and small-scale farmers in developing countries face multiple, interlinked risks that undermine productivity (Komarek et al., 2020). These farmers are particularly vulnerable to climate variability and food price shocks due to their reliance on rain-fed agriculture, dependence on imports, limited resources, and socioeconomic constraints (Morton, 2007; Okou et al., 2022). Agricultural risks are distinct in that they arise from diverse sources, vary in frequency and scale, affect farming activities in different ways, and often reinforce one another along the

agricultural value chain (Mwongera et al., 2019). This complexity makes risk management particularly challenging. No single strategy can effectively address all risks; farmers must therefore combine multiple approaches. In this context, farmers' risk perceptions and preferences play a crucial role in shaping their choice of risk management strategies and technologies. Adoption ultimately depends on farmers first recognizing the risks they face and their potential consequences and then evaluating available options through the lens of their risk attitudes and behavioral tendencies (Feyisa et al., 2023).

Though a lot has been documented on risk, there are gaps in the literature when it comes to agricultural risk, their perception by farmers, and management. For example, focus is usually on production risks, yet farmers also face other risks such as institutional, financial, technological, and personal risks, which shape adoption decisions (Komarek et al., 2020). The second gap relates to selection of technologies and their attributes. Though the expectation is that farmers should select technologies that maximize their returns, poor households frequently avoid modern, productivity-enhancing technologies due to the risks they entail and opt instead for low-risk, lower-return options. A clear illustration of this tendency can be seen in the adoption of improved crop varieties and index insurance.

Improved crop varieties that are drought tolerant, water efficient, or resistant to pests and diseases have the potential to boost productivity (and quality) under adverse conditions, yet adoption rates remain low in sub-Saharan Africa (SSA), even when the varieties are available (Acevedo et al., 2020). Moreover, turnover rates for these varieties are low (De Groote & Omondi, 2023). A similar pattern is observed for index insurance, a market-based risk management tool capable of protecting farmers against a range of shocks but its potential remains largely unrealized, primarily due to low demand (Kramer et al., 2022). The main drivers of the low demand include

basis risk, limited understanding by farmers, lack of trust, liquidity constraints, and the narrow scope of many available products (S. A. Cole & Xiong, 2017; Lichtenberg & Martinez, 2022; Platteau et al., 2017).

1.3. Agricultural extension in SSA

Small-scale farmers in SSA primarily receive information about agricultural innovations and technologies through agricultural extension services (Anderson & Feder, 2007; Cook et al., 2021). Agricultural extension is widely regarded as a public good, ideally provided by governments (Maertens et al., 2021). However, following the structural adjustment programs of the 1990s, many SSA governments significantly reduced public spending, including in provision of extension services (Heidhues & Gideon, 2011). This led to an under-resourced and inefficient extension system that struggles to meet farmers' needs (Bridle et al., 2020). Many extension officers lack access to regular training that would enable them to respond effectively to the evolving information demands of farmers. Moreover, they often face limited facilitation and weak incentives, which further hinder their capacity to disseminate agricultural technologies effectively especially in rural areas. The extension officer-to-farmer ratio in SSA is one of the largest globally, with a single officer typically responsible for between 5,000 and 10,000 farmers (AGRA, 2020).

In addition to the challenges to the extension system in developing countries, evidence on the effect of information transmission on adoption is still inconclusive in the literature. Some studies highlight the importance of training and extension (see Takahashi et al. (2020) for a review), but others find limited effects, especially when it comes to actual technology adoption (Harou et al., 2022; Leight et al., 2022; McKenzie, 2021). Kaiser & Menkhoff (2022) argue that one way to increase the efficacy of extension is finding alternatives to the conventional training and visit (T&V) and descriptive (lecture-based) information delivery. Some alternatives include

farmer-to-farmer technology extension (Nakano et al., 2018), the use of incentives to motivate dissemination of information through social learning (Balew et al., 2022; Benyishay & Mobarak, 2019; Shikuku et al., 2019), and in recent years, the use of digital platforms and ICTs to address the challenges to conventional extension (Spielman et al., 2021). Though some of these approaches have shown promise, they have not been effective in bridging the information gap (Bridle et al., 2020; Harou et al., 2022; Norton & Alwang, 2020), hence the need for further research in this area.

The effectiveness of any information intervention depends on several interconnected factors: who communicates (Arslan et al., 2022), the style and medium through which the information is delivered (Dzanku et al., 2020; Maertens et al., 2021; Van Campenhout, 2021); how the information is framed (Balew et al., 2025; Hobbs, 2022; Szaszi et al., 2022); and the nature and complexity of the technology (Dessart et al., 2019; Hörner et al., 2022). The focus of this thesis is on the style of learning and framing. The low literacy levels of most small-scale farmers might explain the ineffectiveness of conventional extension approaches.

1.4. Informal markets and food safety

Markets play a pivotal role in small-scale agriculture, both as sources of inputs and as outlets for farm output (Ma et al., 2024). They form a crucial link in the adoption of sustainable agricultural practices by small-scale farmers and in driving economic transformation (Liverpool-Tasie et al., 2020). One of the key objectives of the structural adjustment programs of the 1980s and 1990s was to liberalize markets and reduce state influence to enhance efficiency (Dillon & Barrett, 2017; Sitko & Jayne, 2014). Yet decades later, market failures remain widespread in the developing world. A large share of agricultural transactions in these countries occurs in informal markets, where actors operate without formal registration, licensing, or enforcement of regulations related to taxation, labor, or health standards (Roesel & Grace, 2014). Such markets often function

outside government health and safety oversight and face significant constraints, including poor infrastructure (de Janvry & Sadoulet, 2020) and high transaction costs (Aker, 2010). In addition, market actors often lack complete information particularly on quality attributes that are not easily observable, and which require specialized testing technologies, whether for inputs (Michelson et al., 2023) or food items (Bai, 2025). In the absence of reliable third-party certification, these conditions can result in "markets for lemons" (Anissa et al., 2021; Bold et al., 2017), where low-quality products dominate (Hoffmann et al., 2019), thus breaking the chain of economic transformation.

This thesis focuses on incomplete information and food safety in the informal food markets of developing countries. Despite its importance for public health and economic growth, food safety is often a low priority in these contexts (Karanja et al., 2022). Limited consumer awareness of the health risks associated with unsafe food, coupled with a low willingness to pay for safer options, has resulted in chronic underinvestment in food safety (Hoffmann et al., 2019). Although food safety regulations exist, enforcement is weak due to limited institutional capacity, overlapping mandates, resource constraints, and the pervasive informality of food markets (Jaffee et al., 2019). Consequently, the economic burden of foodborne diseases is heaviest in developing countries, which account for roughly 75% of the global foodborne disease burden (Grace, 2023; Jaffee et al., 2019).

In settings like these, observable quality attributes such as the physical appearance of food may serve as proxies for unobservable attributes like safety at the point of purchase (Bold et al., 2022; Do Nascimento Miguel, 2024). Generating and disseminating such information could be a cost-effective alternative to certification schemes or frequent laboratory testing. However, a critical missing link is that market actors often do not know the correlation between observable and

unobservable attributes, and there is no conclusive evidence that using observable traits as signals can stimulate demand and supply for high-quality food in informal markets.

1.5. Overarching objective and research questions

In the theory of change underpinning this thesis, the adoption of productivity-enhancing and effective risk management technologies is central to economic transformation in Kenya and other low-income countries. As productivity rises, farm incomes are expected to increase, enabling small-scale farmers to diversify into alternative livelihood activities and gradually reduce reliance on agriculture, thereby lowering the share of households primarily engaged in subsistence small-scale farming. Technology adoption, however, is shaped by a set of interrelated factors that constitute the focus of this thesis. The overarching objective is to examine how risk perceptions, technology attributes, information, and dynamics in informal markets influence the adoption of agricultural innovations. Specifically, the thesis addresses the following research questions:

1) *Chapter 2:* What are farmer perceptions of agricultural risks in Kenya and which risk attributes matter for men and women?
2) *Chapter 3*: Are dairy farmers willing to pay for improved forage varieties and does the WTP for variety attributes align with perceived local risks?
3) *Chapter 4:* Are farmers' preferences for one index insurance product consistent with farmers' willingness to pay when farmers are exposed to an objectively equal alternative product?
4) *Chapter 5:* Does the style of learning (game-based verses narrative-based) influence effectiveness of extension and adoption of index insurance by small scale farmers?
5) *Chapter 6:* Can information (on the use of observable attributes as proxies for unobservable quality attributes) influence the demand and supply of quality food in informal markets?

1.6. Methods

1.6.1. Cross-sectional survey (design)

Cross-sectional studies analyze data collected from a population at a single point in time and may be either descriptive or analytical in nature (Wang & Cheng, 2020). Descriptive cross-sectional studies aim to characterize a population, for example, by documenting knowledge, attitudes, or perceptions. Analytical cross-sectional studies, in contrast, seek to identify associations between outcomes of interest and population characteristics (Kesmodel, 2018). Although cross-sectional studies are relatively inexpensive and easy to implement, careful attention is required in their design, particularly with respect to sampling strategies, sample size determination, and the measurement of key variables.

Chapter 2 of this thesis draws on a cross-sectional study conducted among farmers in Machakos County, one of Kenya's arid and semi-arid regions. The objective of the chapter was to examine farmers' perceptions of agricultural risk and generate insights to inform subsequent chapters. I aimed to assess whether risks beyond production-related domains are also important to farmers, and whether perceptions of risk are shaped by more than just likelihood and severity. Accordingly, the analysis focused on associations (correlations) between risk attributes, risk domains, and farmers' perceptions. These findings provide the conceptual foundation for the lab-in-the-field experiment presented in Chapter 4.

To minimize potential sources of bias, we employed a systematic sampling approach to obtain a sample representative of a typical farmer in an arid region of Kenya and used a sufficiently large sample size to enable reliable statistical inference.

1.6.2. Experimental auctions

Contingent valuation (CV) methods are widely used to assess (future) demand and elicit individuals' willingness to pay (WTP) for new or unfamiliar products (Penn & Hu, 2018). A persistent critique of CV approaches concerns the sensitivity of WTP estimates to the elicitation mechanism and the well-documented divergence between willingness to pay and willingness to accept (Hausman, 2012; Johnston et al., 2017). Among the available mechanisms, the Becker–DeGroot–Marschak (BDM) procedure remains popular because it is known to be incentive-compatible (Berry et al., 2020; Burchardi et al., 2021; S. Cole et al., 2020) and reveals richer information about individual demand compared to other mechanisms. However, like the other CV approaches, WTP from BDM is sensitive to hypothetical and non-hypothetical settings (Penn & Hu, 2018), and field implementation may be constrained by game-form recognition failure, especially among populations with limited literacy (Cason & Plott, 2014).

In chapters 3 and 4 of this thesis, I rely on the BDM mechanism while adopting several design features to attenuate sources of bias. In Chapter 3, WTP for improved forage varieties is elicited using the actual products in farmers' natural environment, thereby reducing hypothetical bias (Harrison & List, 2004). To limit social desirability bias, I incorporated a cheap-talk script designed to encourage "truth telling" (List & Price, 2016). To mitigate risks of game-form recognition failure, participants completed a practice round using a familiar, low-stakes product (ordinary soap) before submitting binding bids.

In Chapter 4, WTP for index insurance products is elicited within a crop-risk game that closely mirrors maize production. The game provides farmers with experiential learning and feedback about the insurance products prior to bidding, a feature shown to enhance attention and potentially reduce hypothetical bias (Boyle et al., 2011). Evidence from related approaches such

as virtual reality addresses hypothetical bias thus improving the reliability of WTP (Fang et al., 2021). As in Chapter 3, a practice round was included to ensure full comprehension of the bidding procedure. Additionally, farmers were randomly assigned to either the BDM mechanism or the take-it-or-leave-it (TIOLI) mechanism, which better reflects how market transactions happen, allowing us to assess and control for potential sensitivity of WTP to the elicitation mechanism.

1.6.3. Lab-in-the-field (framed) experiments

Lab-in-the-field experiments combine key features of laboratory and field experiments to study agents' behavior in "real-world" settings (Gneezy & Imas, 2017; Harrison & List, 2004). The laboratory elements allow researchers to maintain control over important aspects of the design while the field experiment elements, especially random assignment, enable researchers to attribute observed outcomes to the manipulated factors (Canavari et al., 2019). Unlike conventional laboratory experiments that rely on student participants, lab-in-the-field experiments involve relevant populations, such as farmers or traders, and are conducted in their natural environments. This design directly addresses a common critique of laboratory experiments: their limited external validity (Falk & Heckman, 2009). As a result, lab-in-the-field experiments can more closely reflect real-world decision-making compared to lab experiments and often offer a low-cost alternative to full-scale field experiments for answering certain policy-relevant questions (Falk & Heckman, 2009; Gneezy & Imas, 2017).

In Chapter 4 of this thesis, I used a lab-in-the field experiment to study how farmers value two objectively equal index insurance products that differ only in their trigger levels. By experimentally manipulating the trigger levels, we elicit farmer valuations and preferences for each product. Random assignment of farmers to the two insurance products allows us to causally attribute differences in valuation and preferences to the product attributes, particularly the trigger

level. Together, these strategies enable us to address key policy questions regarding insurance demand (preferences) and pricing (valuation). Furthermore, the sample used in Chapter 4 of this thesis is sufficiently large, thus addressing another common critique of lab-in-the-field experiments, namely small sample sizes.

1.6.4. Randomized controlled trials (RCTs)

The central challenge in estimating the impact of a program or intervention is the identification of a credible counterfactual. Because an individual cannot simultaneously be observed in both treatment and non-treatment states, simple before–after comparisons generally fail to provide reliable causal estimates (Duflo et al., 2007). This problem is compounded by selection bias, which arises when individuals who receive an intervention differ systematically from those who do not.

Randomized controlled trials (RCTs) are widely regarded as the gold standard for causal inference because random assignment mitigates selection bias (Angrist & Pischke, 2008). By balancing both observed and unobserved characteristics across treatment and control groups, randomization ensures that any post-intervention differences can be attributed to the intervention itself (Banerjee, 2020). External validity of RCTs typically rests on the assumption that treatment effects are stable across comparable populations and settings (Banerjee, 2020). As such, extrapolating results beyond the study sample requires careful consideration of contextual factors and, in some cases, the aggregation of evidence from multiple studies (Deaton & Cartwright, 2018).

This thesis incorporates two RCTs, presented in Chapters 5 and 6. Chapter 5 evaluates the effectiveness of game-based learning relative to conventional narrative-based extension approaches for farmers in Kenya, focusing on index insurance. Farmers were randomly assigned

to either a game or a narrative intervention. To ensure a valid comparison, the narrative information was "worked into" game instructions so that the two approaches differed only in their experiential components. Data were collected in two waves: a baseline household survey used for randomization, followed by an intervention phase during which the treatments were administered and post-intervention outcomes measured.

Chapter 6 presents an RCT conducted among maize traders and consumers in informal markets in Meru County, a known hotspot for aflatoxin contamination. Randomization took place at the market level to reduce spillovers. The sampling frame was constructed using a list of markets obtained from the County Department of Trade, supplemented with short verification calls to key informants—typically area chiefs—to confirm market names, main market days, and the presence and number of retail maize traders. Markets without reachable contacts or without maize traders were excluded, resulting in a final sample of 90 markets. These were randomly assigned to either an information-intervention or a control group, with stratification by subcounty and market size to improve covariate balance. Treatment markets were further randomized into either a positive or negative frame of the intervention. Data collection occurred in three rounds: a baseline survey in July 2022, a first follow-up survey three weeks after the intervention, and an endline survey three months after the intervention. The intervention consisted of a six-week information campaign delivered weekly in each treatment market.

1.6.5. Multivariate modelling

Multivariate modelling involves simultaneous analysis of multiple variables (Hair et al., 2020). Structural equation modelling (SEM) is one commonly used multivariate approach, and it exists in two main forms: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). While CB-SEM is primarily suited for theory testing, PLS-SEM is more appropriate for

theory development in exploratory research, making it well suited for the analysis of risk perceptions in Chapter 2 (Burns et al., 1993). PLS-SEM offers several advantages: it is a non-parametric technique that does not require assumptions such as multivariate normality, it performs efficiently with complex models, and it accommodates both reflective and formative constructs (Hair et al., 2019)

1.6.6. Economic modelling

Economic modelling forms an essential component of the methodological approach used in this thesis. In economic modelling, models serve as simplified representations of economic reality that highlight key relationships between economic variables and generate predictions about how individuals (economic systems) are expected to behave under different conditions. This thesis applies economic modelling both as a conceptual tool and as an empirical guide for structuring the analysis.

While neoclassical models have traditionally underpinned economic analysis, they often rely on simplifying assumptions that may not reflect real-world decision-making. In response, behavioral economics has progressively refined these models to incorporate psychological insights and produce more realistic behavioral predictions (Gilboa et al., 2014). This methodological evolution is especially relevant in contexts—such as smallholder agriculture—where risk, uncertainty, and limited information can generate behavior that departs from standard theoretical predictions.

Chapter 2 adopts this behavioral-modelling perspective by examining how farmers form perceptions of agricultural risk. Expected utility theory conceptualizes risk solely in terms of likelihood and severity, suggesting that perceptions should be driven predominantly by these two attributes. However, small scale farmers in low-income countries face multiple layers of

uncertainty that extend beyond classical definitions of risk. Guided by behavioral economic frameworks, the empirical strategy in Chapter 2 includes additional risk attributes and risk domains to capture these broader dimensions. The cross-sectional design is therefore complemented by a modelling approach that allows risk perceptions to be shaped by factors beyond the expected utility framework.

Economic modelling also informs the analysis in Chapter 4, which examines farmers' willingness to pay for two index insurance products that are objectively equivalent in expected payouts but differ in their trigger structures. While neoclassical theory assumes stable, complete, and internally consistent preferences, evidence highlights systematic violations of these assumptions, such as preference reversals (Ariely et al., 2003). Behavioral heuristics and biases are known to play an important role (Kahneman et al., 1982). Incorporating these behavioral insights into the modelling framework helps explain why farmers may value two "equivalent" insurance products differently.

1.6.7. Econometric analysis

As noted earlier, economists are interested in understanding relationships between economic variables, and econometrics provides the tools to quantify these relationships. In this sense, econometrics entails economic theory, empirical data, and statistical methods (Verbeek, 2017). Econometric analysis typically begins with a theoretical proposition—formulated as a testable hypothesis—followed by the identification and specification of dependent and independent variables, and an expectation regarding the direction of the relationships between these variables (Greene, 2020). Importantly, econometrics accommodates the inherent randomness of human behavior.

Econometric analysis encompasses a range of methodological approaches that account for both behavioral randomness and the structure of different types of data. These include regression analysis, time-series methods, panel data techniques, and experimental or quasi-experimental designs. In this thesis, I employ both regression-based and experimental approaches to test the hypotheses developed in the various chapters. For instance, in Chapter 3, I use regression analysis to examine farmers' willingness to pay for improved forage varieties and to explore the associations between WTP and farmer characteristics. In Chapters 4 through 6, regression analysis is used primarily for causal inference, leveraging data generated through experimental interventions.

1.7. Roadmap and thesis contributions

The remainder of the thesis is organized as follows. Chapter 2 examines farmers' risk perceptions and the risk attributes that matter for men and women. This chapter challenges two common practices in the study of agricultural risk: the tendency to focus primarily on production-related risks at the expense of other risks that farmers face, and the treatment of risk solely as a function of magnitude and probability. Such a narrow scope can limit the relevance and (cost) effectiveness of risk management strategies. I find that risks outside the production domain also matter, particularly because risks along an agricultural value chain are diverse and interlinked. I also find that attributes beyond likelihood and severity such as "perceived controllability" play an important role in shaping farmers' perceptions of risk. This perspective is supported by evidence that farmers do not always behave in ways consistent with expected utility maximization, the dominant framework for analyzing decisions under risk and uncertainty, where probabilities and magnitude play a central role. The empirical results reveal gender differences in certain dimensions of risk perceptions. This chapter underscores the importance of considering heterogeneity in how

farmers perceive risks when designing or recommending risk management technologies to small scale farmers. Blanket recommendations may not be effective.

Chapters 3 and 4 build on the findings from Chapter 2 by linking farmers' risk perceptions to their preferences for risk management strategies and technologies. Chapter 3 evaluates dairy farmers' willingness to pay (WTP) for improved forage varieties and dried livestock feed. These varieties have the potential to address the widespread problem of livestock feed shortages in sub-Saharan Africa due to their high productivity and their resistance to production-related risks, including pests and diseases, as well as tolerance to abiotic stresses such as drought and flooding (Creemers & Aranguiz, 2019). However, as mentioned earlier, the adoption of improved forage varieties is low as for other crops. While several studies have examined trait preference for staple crops (Kassie et al., 2017; Lybbert, 2006; Mastenbroek et al., 2021), far fewer have assessed preferences for improved forage varieties, and the limited existing evidence exhibits methodological shortcomings in the elicitation. This chapter therefore fills an important knowledge gap. I find that farmers' WTP was below market prices for most varieties, although WTP was higher for varieties with which farmers had prior experience. There were no significant differences in WTP across closely related varieties, despite each variety possessing at least one unique trait (e.g., water efficiency, tolerance to drought, tolerance to waterlogging, quantity of forages, and time to maturity). This suggests that farmers were unable to differentiate and appropriately value the more subtle improvements in each of the improved varieties. Taken together, these findings underscore the importance of targeted information and promotional efforts that aim to raise farmers' awareness of the specific benefits of individual varietal traits and their alignment with local risk conditions, to enhance ("the right") adoption.

Chapter 4 investigates farmers' WTP and switching behavior between actuarially identical single-peril (SP) and multiple-peril (MP) index insurance products. Conventional single-peril products are often limited in relevance because farmers face multiple salient risks, while traditional multiple-peril products tend to be expensive, raising affordability concerns. Dependent on farmer preferences, the innovative multiple-peril product examined in this chapter can address both challenges. I find no significant difference in WTP for the SP and MP products, suggesting that, on average, farmers value the two products equally, implying risk neutral preferences. However, switching behavior reveals a different pattern: 61% of farmers initially assigned to the SP product wanted to switch to the MP product, compared with only 37% of those assigned to the MP product who wished to switch to the SP product. The switching seems to be consistent with preferences shaped by heterogeneous subjective risk perceptions and precautionary behavior such as sensitivity to tail risk, dimensions not fully captured by price alone. These findings suggest that insurance products tailored to farmers' heterogeneous risk perceptions and profiles (as demonstrated in chapter 2), particularly those offering protection against rare but severe losses, may achieve higher uptake. The results also indicate that WTP alone may be insufficient to fully characterize farmers' preferences for risk management innovations.

Chapter 5 of this thesis evaluates the effectiveness of game-based learning as an extension approach vis a vis the conventional narrative-based approach used by extension agents with a focus on index insurance, one of the most ill-understood risk management strategies by farmers (Ahmed et al., 2020). Game-based learning entails the use of games for educational purposes (Dernat et al., 2023; Krath et al., 2021). Our focus differs from Cai & Song (2017) because we consider basis risk. We randomly vary exposure to basis risk in our game, setting the paper apart from Jensen et al. (2018) who use observational data to study how realized basis risk affects purchase of index-

based livestock insurance. Our paper is closest to Janzen et al. (2021), who provide a basic (narrative-based) training to *all* participating farmers and then invite a random subsample of these subjects to also engage in their game. Instead, we randomly assign our subjects to either a conventional narrative-based extension session *or* a game-based learning experience (or a control group), enabling us to isolate the game effect. I find that game-based learning was more effective as an extension tool compared to the narrative-based extension. The effectiveness of games as extension tools lies in their ability to illustrate goals and their relevance, nudge users through guided paths, give users immediate feedback, reinforce good performance, and simplify content to manageable tasks (Landers et al., 2018; Plass et al., 2015). Games can mimic "realities", carry the player to those "realities", and induce reflection on experiences during the game. Finally, since playing games can be "fun", game-based learning may trigger intrinsic motivation and enable individuals to concentrate for longer, especially when dealing with topics that otherwise are less attractive (Plass et al., 2015).

Chapter 6 examines whether providing consumers and traders in informal markets with information on the relationship between maize kernel integrity and aflatoxin contamination leads to quality upgrading by traders, consumers' willingness to pay premiums for higher-quality maize, and increased sales for traders offering safer maize. At the time of the study, this relationship was not widely known among market actors; thus, if effective, the intervention could provide a low-cost, market-based alternative to quality assurance in informal markets characterized by limited oversight and third-party verification. The chapter is motivated by two main strands of evidence. First, research shows that consumers are willing to pay premiums for superior observable food quality traits (Jones et al., 2016) and for credible quality signals such as certification (Bai, 2025; Löwenstein et al., 2024; Prieto et al., 2021; Tran et al., 2022). Second, providing consumers with

credible information on unobservable food quality has been shown to influence demand and pricing in informal food markets (Kariuki & Hoffmann, 2022; Lin et al., 2024). I find that three weeks after the intervention, maize in treatment markets contained 13% fewer damaged kernels and was 11 percentage points less likely to exceed the low-quality benchmark (>10% damaged kernels). Prices were unchanged, but sales volumes fell, driven by reduced sales of poor-quality maize. By the second follow-up, about two months later, these effects had faded. Results suggest that low-cost information can induce short-run improvement in food quality in informal markets, however, sustaining these gains likely requires repeated campaigns or complementary incentives.

Chapter 2

Farmer perceptions of agricultural risks; which risks attributes matter most for men and women

Abstract

Analyses of farmers' risk perceptions typically focus on production risks, viewing risk as a function of likelihood and severity. However, this approach is limited, given the wide range of risks farmers face and the importance of additional risk attributes. In this chapter, we extend the analysis of risk perceptions beyond production risks and beyond the traditional emphasis on likelihood and severity. We begin by characterizing agricultural risks and identifying their main sources and consequences. We then analyze risk perceptions using partial least squares path modelling, allowing us to capture the relative importance of different risk attributes. Specifically, we identify the most salient risks and attributes shaping farmers' perceptions and examine gender differences in these perceptions. The results show that perceived severity and the ability to prevent a risk are the most influential factors shaping overall risk perceptions. Moreover, while probabilities (likelihoods) tend to matter more to men, perceived ability to prevent risks is more important to women for certain risk types. Low crop yields and fluctuating input prices exert the greatest total effects on overall farmer risk perception. These findings highlight the need for agricultural risk analysis to incorporate dimensions perceived controllability, underscores the policy importance of input price stabilization and redress of the persistent yield gaps in small-scale agriculture.

Keywords: Agricultural risks; Risk perceptions; Risk management; Locus of control; Structural equation modelling; Uncertainty; COVID-19; Kenya

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2.1. Introduction

The role of risk and uncertainty perceptions on small-scale farmers' decisions is increasingly acknowledged (Siegrist & Árvai, 2020). However, the lens through which risk and uncertainty are addressed in agriculture is blurry in several ways. There are three issues that deserve consideration for a more comprehensive understanding of the risk perceptions and behavior of farmers.

First, risk and uncertainty are conventionally addressed as functions of probabilities, where according to Knight (1921) the former is associated with known probabilities while the latter is associated with unknown probabilities. In classical economics, expected utility theory – which dominates the literature on decision making under risk – considers risk as a product of likelihood and stakes (magnitude), where choice is a result of an individual's assessment of an event's magnitude and likelihood (Loewenstein et al., 2001). However, empirical literature shows that individuals do not always follow the tenets of expected utility in making decisions under risk (Dhami, 2016), especially in the absence of insights about objective probabilities like in the case of small-scale farmers in developing countries. In addition, in some cases, even with probabilities, individuals may portray probability insensitivity (Loewenstein et al., 2001), while in other cases the probabilities matter less on how individuals assess risk (Wilson et al., 2019). Such evidence warrants extending risk and risk perception analysis beyond likelihood and stakes, which are just a fraction of risk attributes.

Second, most research on risk in agriculture focuses on production risks, yet farmers face several other types of risks. Komarek et al. (2020) characterize risk into five types namely production, market, financial, institutional, and personal. These risks are interlinked with each other in the sense that some risks may cause some others, while others reinforce each other as

shown in the analysis by Ansah et al. (2020). This interlinked nature of agricultural risks complicates both the analysis and the design of risk management tools for the farmers. Methodologies that can disentangle the complex nomological networks of risks, risk sources and risk attributes are needed to enhance understanding of agricultural risk and ultimately management.

Third, each risk is associated with several attributes, either objective or subjective. The attributes (characteristics) include controllability, voluntariness, degree of uncertainty, catastrophic potential (Martin et al., 2009), and consequences, familiarity and sources of the risk (Renn, 1989). According to the psychometric paradigm of risk analysis, the attributes of risk influence risk perceptions (Breakwell, 2015). For this reason, people have as many risk perceptions as there are risks, contexts, and situations around them. Notwithstanding, current analysis of attributes of the many risks in agriculture, and their role in shaping risk perceptions of farmers, is limited.

The objective of this paper is to shed more light on the concept of risk and uncertainty from the perspective of a small-scale farmer in a developing country considering the issues discussed above. A better understanding of farmer risk perceptions is important for informing on the appropriate design of risk management tools relevant to small-scale farmers to support their better risk management. Our work builds on Komarek et al. (2020), Ansah et al. (2020), Weber et al. (2002), and Wilson et al. (2019). The first two studies highlight the pertinence of assessing multiple agricultural risks. Komarek et al. (2020) specifically shows that though smallholder agriculture is challenged by many risks, most of the research focus on production risks even in the absence of empirical evidence justifying such a narrow focus. Ansah et al. (2020) further justify the assessment of multiple agricultural risks by showing that risks interact to amplify their effects on small-scale farmers. The study concludes that focusing on a single risk may misguide risk

management interventions. Weber et al. (2002) on a different vein show that individual's attitudes towards risk differ across various risk domains, hence the need to assess the specific risk attitudes and perceptions in the concrete context of the small-scale farmer that is characterized by many simultaneous risks, risk domains. Lastly, Wilson et al. (2019) tackle important confounding issues in the study of risk perceptions. Most importantly, the authors argue that risk is multi-dimensional, and such multi-dimensionality calls for approaches that go beyond consideration of just likelihood of-, and exposure to risks. We follow this approach and model risk perceptions as a hierarchical construct. Specifically, we seek to assess how multiple risks, risk attributes, and risk domains interact to shape risk perceptions of farmers.

To achieve this objective, our concept of risk encompasses all dimensions given by Hardaker (2000) namely risk as the variation in an outcome of interest, probability of unwanted outcomes, and uncertainty of outcomes. In this sense, risk' entails both risk and uncertainty. Our use of risk to also include uncertainty is further justifiable in our context for two more reasons. First, our subjects, namely small-scale farmers in a developing country do not differentiate between the two concepts since they use the same term in their local dialect to mean both risk and uncertainty, and second, most farmers do not have objective probabilities (imperfect information) of most of the events related to agriculture. Instead, the farmers impute subjective probabilities.[1] The substitution of objective probabilities, which are usually weighted in actual decision making (Kahneman & Tversky, 1979), with subjective probabilities blur the intuitive difference between the concepts of risk and uncertainty.

[1] Important to note is the difference between probability weighting and subjective probabilities. Weighted probabilities are surrogates of objective probabilities while subjective probabilities are probability substitutes, which individual form where there are no objective probabilities.

Our analysis is divided into two distinct but related parts. In the first part, we provide a characterization of the risks experienced by the farmers. We adopt the characterization of risk by Komarek et al. (2020) that divide agricultural risks into five main types, which we call domains. We add a sixth domain namely consumption risks based on the evidence from Ethiopia regarding its role on technology adoption (Dercon & Christiaensen, 2011).

We proceed by mapping out the main sources, severity, perceived ability to prevent (cope with), and the main consequences of every risk in each of the six domains. For the purposes of discussion, we report on findings for the most problematic (important) risks only. Importance in this case is based on a ranking of the risks done by the farmers themselves during the survey. Details about the other risks are given in Appendix Table 2.4.

In the second part of the paper, we use 435 of our respondents to assess the most important risks, and the most important risk attributes contributing to risk perceptions of farmers using partial least squares structural equation modelling approach (PLS-SEM). We focus on three problematic risks namely low crop production, fluctuating input prices, and reduction in agricultural incomes as discussed in detail in the subsequent sections. It is noteworthy that all farmers included in this second part of our analysis have experienced the three risks in the previous five years from the time we conducted our survey.

2.2. Theoretical framework

Risk perceptions, which refer to how individuals relate, collect, select, and interpret signals about uncertain impacts of events, activities, or technologies (Wachinger et al., 2013) are influenced by three broad factors namely individual characteristics, and risk attributes (Lindell & Perry, 2012; Siegrist & Hartmann, 2020), and trust in communicating institutions (Sullivan-Wiley

& Short Gianotti, 2017). Individual characteristics such as gender, age, education, and wealth, and other innate attributes create the lens through which a person assesses various risks, and the attributes of them.

Two main ontologies explain how individuals assess (perceive) risk and associated risk attributes, namely risk as a "feeling", and risk as an "analysis" (Slovic & Peters, 2006). Risk as a feeling, advanced by Loewenstein et al. (2001) involves emotion, intuition, and instinctive reactions to uncertain events. Risk as analysis on the flip side involves logic and reason. Unlike in risk as feeling assessment, individuals systematically and objectively process information about a risk in the analysis. Theoretically, since some risk situations may be greatly consequential, individuals should be more objective on how they assess the situations and properly act either to cope/prevent the risk from happening or avoid it. However, evidence shows that the risk as feeling tends to override the risk analysis in actual decision making (Breakwell, 2015). Two related theories on cognitive processing, namely Epstein's experiential and rational modes (Epstein, 1994), and Kahneman's system 1 and 2 (Kahneman, 2011) explain the dominance risk as feeling in actual decision making. The experiential mode (system 1) operates automatically, is more rapid, encodes reality in concrete metaphors and narratives, and is mediated by experience, while the rational mode (system 2) devotes effort to more complex computations. System 1 originates impressions, ideas, and feelings, which form the blue-prints of judgement of system 2 (Kahneman, 2011). System 2 uses various mental strategies and heuristics in reducing complex information to manageable levels.

Reduction of the complex risk environment depends on the degree to which an individual's mental strategies or heuristics provide readily accessible and coherent beliefs about certain risks. In the language of Lindell & Perry (2012), when someone has a certain schema (heuristic) – a

generic knowledge structure defined by instances, attributes that differentiate these instances, and interrelationships among the attributes – beliefs about a risk encompassed by that schema are rapidly accessed to produce an overall judgement that is congruent with the available information about the risk situation. Some of the heuristics discussed in literature include the availability heuristic, anchoring, and the affect heuristic. The availability heuristic refers to the tendency of people assessing events based on the ease with which instances or occurrences are easily recalled (Kahneman et al., 1982). Anchoring refers to the tendency of people to make estimates starting from a certain reference that is adjusted to give a final answer. For example, people are likely to use historic probabilities to make judgments about future likelihoods of risks, or historic input prices to infer to possible prices in the future. Lastly, the affect heuristic involves the instinctive and intuitive reactions to risk (Loewenstein et al., 2001; Slovic & Peters, 2006).

Knowledge about the role of heuristics in processing information under risk and uncertainty based on the beliefs, ideas, and feelings advanced by the experiential mode is an impetus for analyzing risk perceptions of small-scale farmers in their context of numerous interlinked risks. Our philosophy assumes that given diverse socio-economic environments of the farmers and diverse psychological states, same set of risk attributes, and same exposure to risk, the farmers' perceptions of the risks will not only differ across certain individuals, but also across risks and risk domains for the same individual. Some literature also points out that there are differences in risk perceptions across groups such as men verses women (Breakwell, 2015). The main driver of the differences in perception being the experiential risk perception, and even though risk perception may not be experiential in some instances, many years of doing agriculture might make some of the farmers' judgements about agricultural risks more automatic, a faculty of the rapid and

automatic experiential mode (system 1). Consequently, some unlikely risk attributes and risks may be viewed as less relevant, or more relevant by the farmers.

Our risk analysis approach tends towards the psychometric paradigm. Risk perception starts from risk attributes to respective risks, risk domain and finally to the overall perception in that order as outlined in Figure 2.1. We build on the framework suggested by Siegrist & Hartmann (2020) though their analysis targets consumers. Noteworthy is that though our analysis does not explicitly consider individual attributes except for gender, we control for them in an extra stage of analysis using a multiple linear regression. We find that the individual characteristics explain less than 10% of the variation in the risk perception, hence we do not discuss the results of this final stage here (see Appendix Table 2.6).

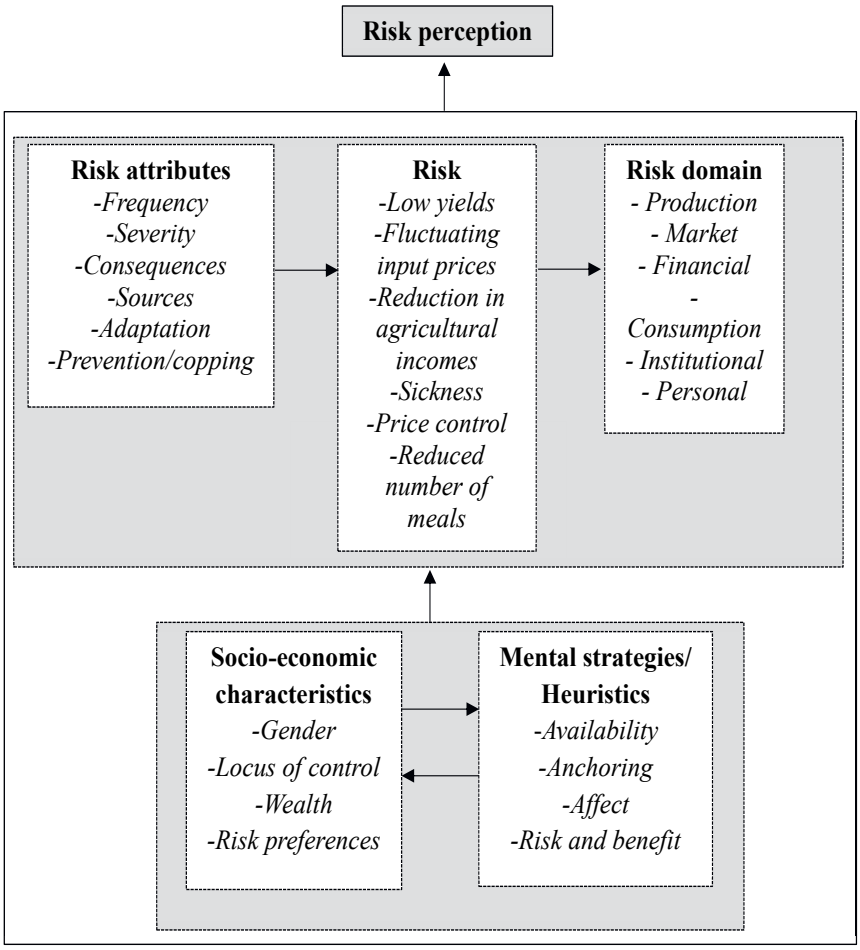


Figure 2.1: Formation of risk perceptions (Authors' conceptualization)

Given this background, we test the following hypotheses non-parametrically:

Hypothesis 1: *Risks under the production domain are not the most important to the farmer*

Most of the research and risk management work is focused on the production domain (Komarek et al., 2020). However, not only is there insufficient evidence to support such a narrow focus, but also insufficient evidence on which specific risks under the production domain matter most. In addition, we hypothesize that other risks in other domains might be even more important to the farmer. We therefore first characterize different risks to assess which is the most important

in each risk domain, and second, we use structural equations to determine the most important risk across domains.

Hypothesis 2: *Historic and future frequencies of risks are not the most important risk attributes to the farmer's perception of risks*

Though risks are associated with several attributes, many studies measure risk perceptions as the product of probability and magnitude (Wilson et al., 2019). Such an approach is limited in agriculture since agricultural risks are associated with many other attributes such as controllability, ability to prevent the risk, consequences, and sources. The risks are also likely to be interlinked. For example, a weather shock may result in low yields, which in turn will result in a reduction in agricultural incomes. Therefore, whether the frequencies matter in how farmers perceive the risks in this complex environment is non-trivial. We are not aware of any studies that empirically assess the role of other risk attributes other than probabilities in forming farmer risk perceptions.

Hypothesis 3: *There are no statistically significant differences in the perception of risk attributes, and the risks themselves between men and women*

Many differences between men and women influence the uptake, and choice of risk management strategies. For example, several studies have documented differences in risk attitudes and perceptions between men and women (Cullen et al., 2018). However, it is not clear from literature how male and female farmers value risk attributes and, whether their perceptions of relationships across risk attributes and the risks are different. We hypothesize that there are no statistically significant differences between men and women when it comes to perception of various risk attributes and relationships across them.

2.3. Relevant literature and definition of concepts

2.3.1. Risk attributes, risk sources, and consequences

Under the psychometric paradigm of risk analysis, risk attributes play an important role in influencing risk perceptions (Breakwell, 2015). A taxonomy of risk and risk attributes exists in literature (Slovic, 1987). The qualitative attributes which include risk sources, consequences, severity, and ability to control (Renn, 1989), relate to how an individual assesses self (feelings and emotions) with respect to the risk. Such an assessment will depend on how clear the various risk and their attributes are understood by the individual.

A challenge arises in the context of agricultural risks since the taxonomy of risk, and attributes such as sources, and consequences is not straight forward. There seems to be no clear distinction of risks, their sources, and consequences in literature. For example, Komarek et al. (2020) identify the broad risk categories namely production, market, financial, personal, and institutional as risk types. Duong et al. (2019) and Harwood et al. (1999) identify them as risk sources. Though there is no empirical evidence of the extent to which such arbitrary taxonomy may limit understanding and management of the risks by farmers, there is a likelihood of such a limitation, not only on the side of farmers but also other stakeholders in agricultural risk management. Nevertheless, it is not our goal to disentangle these issues in this paper, but for the sake of maintaining clarity, we endeavor to explain our use of the terms risk type (risk domain), risk sources, and consequences. Our classification of risk types and risk sources is as in Komarek et al. (2020).

For risk sources, we also consider second level sources, for instance in cases where a weather-related hazard causes low crop yields, and low crop yields in turn cause a reduction in agricultural incomes. In this sense, low crop yield is also a source of risk (second level). The final

implication of the risk on any aspect of a farmer's life forms the consequence. Noteworthy is that some risks such as reduction in agricultural incomes can be considered as consequences as well. Following the classification we have outlined, we briefly discuss the risks and their attributes in the subsequent paragraphs.

Production risks entail all risks relating to the production stage. Therefore, risks relating to quality of inputs, farm equipment, produce at the field, and off the field (post-harvest) all fall under the production category. Risk sources in the production domain will include, weather related shocks, pests and diseases, and input quality.

Market risks relate to all risks entailing acquisition of the inputs, and marketing of produce. The risks include fluctuating prices, and poor access to markets (in cases of physical markets). Sources of market risks include information asymmetries, and weather shocks. Favorable weather may for instance cause an upside risk, which in turn will cause gluts in the markets that result in low output prices.

Financial risks relate to all risks entailing financing of farm operations, and sources include variation in wage rates, interest rates, and access to credit. Current Covid-19 restrictions can be considered as additional sources of financial risks.

Institutional risks include risks relating to formal and informal laws and regulations in the agricultural sector such as tenure security, price controls (or lack of them), and export or import tariffs. Regulations on land use, and policies on for instance irrigation are all considered institutional risks.

We incorporate *consumption risk* based on the evidence from Ethiopia on the role of consumption risk in technology adoption (Dercon & Christiaensen, 2011). Though consumption risk in the mentioned paper relates more to its financial meaning of the uncertainties associated

with investing in something in expectation of higher returns in the future instead of current consumption, we use the term to relate more to food security since food expenditure constitutes the largest portion of household expenditure in Kenya. Consumption risks include reduced number of meals, reduced quantities of food, food contamination, and food lacking sufficient nutrients. Some of the sources of consumption risk include climate hazards and volatility of food prices.

Lastly, *personal risks* relate to an individual's health and social problems, which affect farm operations. Some of the personal risk include illness, death, and divorce.

2.4. Materials and methods

2.4.1. Study site

We used survey data collected from four sub-counties of Machakos County in Kenya namely Machakos Central, Yatta, Kathiani and Mwala. Machakos County is one of the arid and semi-arid counties of Kenya. Although agriculture is the main economic activity in the county, the sector is vulnerable to many shocks including climate shocks especially droughts and dry spells. The county has two rain seasons: the October and December short rains, and the March and May long rains. The short rains season is the most important for crops. The county receives about 500mm to 1250mm of rainfall annually with disparities in temporal distribution. The study sub-counties were purposively selected to have a representation of the variation in rainfall, and agricultural activities for the county and the whole country in general. On one hand, Mwala and Yatta sub-counties where livestock production is dominant are very dry. The two sub-counties usually receive less than 500mm of rainfall annually. On the other hand, Machakos Central and Kathiani are wet sub-counties most suitable for crop production.

2.4.2. Sampling

We surveyed 792 farmers in November and December of 2020. Important to note is that we needed a minimum of 768 participants from our sample size calculations assuming a 5% margin of error, a confidence interval of 95%, and a 50-50 distribution of men and women in the population. Participants were randomly selected. The random selection was systematic in the sense that we did random walks skipping at least three households to the next participant. The starting point was a point agreed upon with the local village administration heads who were our contacts at village level. The farmer's willingness to participate in the survey and availability also determined the number of households skipped to the next participant as well as the starting points. For each of the household, we interviewed the household head, or the person who made agricultural decisions if it was not the household head. Figure 2.2 shows a map of the study area, and the geo-positioning system (GPS) points of the sampled farmers.

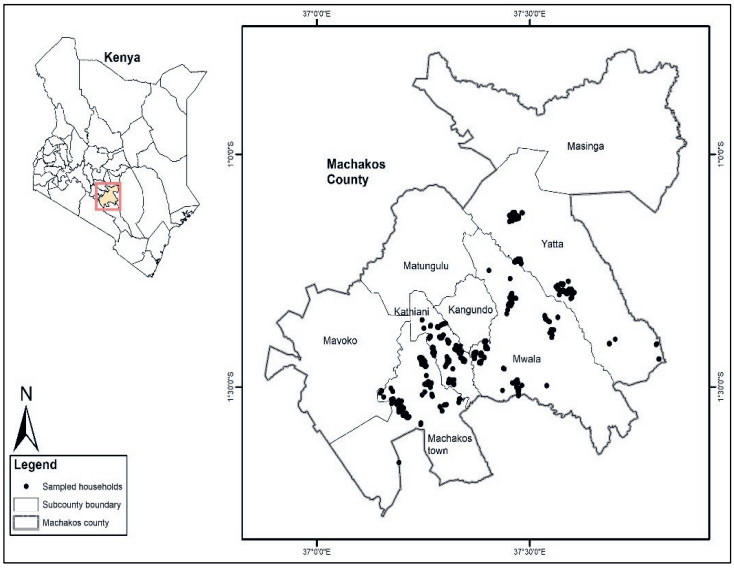


Figure 2.2: Study area and sampled households

2.5. Empirical approach

Each of the farmers was asked questions on socio-economic characteristics (individual attributes), and risk attributes as we discuss below. We chose the attributes based on direct or indirect relevance to risk perceptions.

2.5.1. Individual and farm characteristics

Individual and farm characteristics that we focused on are: sources of capital for financing farming, household information (household size, education level, age, and employment), welfare and wealth status (asset counts, household dietary diversity, annual expenditure, and satisfaction with life (Appendix 2.1), non-cognitive skills (locus of control), whether directly affected by Covid-19, reported propensity to take risks, and risk preferences (risk aversion).

2.5.2. Dietary diversity

Dietary diversity was measured using the 24-hour recall questions adopted from the Food and Agriculture Organization (Food and Agriculture Organization, 2010). The final dietary diversity score is obtained by summing up the number of food groups the respondent consumed. The score ranges from 0 to 12. Individuals with higher values are considered to have a higher dietary diversity. Dietary diversity is of relevance in risk perceptions especially for the consumption domain.

2.5.3. Locus of control

We adopt Rotter's brief scale in measuring the farmer's locus of control (Lumpkin, 1985), but also incorporate five more items to make a total of 11 items (see Appendix 2.1). Locus of control is the extent to which people believe that the outcome and circumstances around them are creations of their choices and decisions (Rotter, 1966). According to this scale, individuals either have an internal locus of control in that they believe that they control their lives and circumstances,

or an external locus of control in that they believe that their lives and circumstances are controlled by strong others. We determine the locus of control score by first, reverse-coding the negatively phrased items, and then finding the difference between the sums of the positively phrased items and those of the negatively phrased items. In this sense, a higher score means that the individual has an internal locus of control, and vice versa. Locus of control has been found to vary with factors that influence differences in risk perceptions such as gender and age (Armaş et al., 2017).

2.5.4. Risk aversion

We adopt the approach by Tanaka et al. (2014) to measure risk aversion. Following this approach, farmers responded to 28 hypothetical questions (series 1 and series 2, each having 14 questions) involving small monetary stakes (Appendix 2.4). We asked the farmer to choose either option A or option B for each of the questions in series 1 and 2. The farmers were allowed to switch only once between option A and option B in each series. The risk game was incentive compatible since farmers played for real money in the last round of the risk game. We use the switching points from series 1 and series 2 to obtain probability weights and risk aversion measures as estimated by Tanaka et al. (2014)[2] who use prospect theory. In prospect theory, value is attached to changes in wealth and not the final asset position as in expected utility theory. We assume a piecewise power function, and Prelec's probability weighting function (Prelec, 1999). The values of σ and α for every possible switching point are provided in Appendix Table 2.2.

Tables 2.1 and 2.2 provide a summary of the characteristics of our respondents based on the variables outlined above. We note that men tend to register higher scores that are significantly

[2] Noteworthy is that our stakes were in Kenyan Shillings. Therefore we factored the stakes in Tanaka et al.(2014) by 3 to make them decently comparable in value to the Vietnamese Dong. In this analysis, we assume that such factoring will not have an impact on the risk parameters.

different from those of women regarding annual household expenditures, asset count, locus of control, and propensity to take risks. There tends to be no difference across the sub-counties except for Machakos sub-county that is statistically significantly different from the other sub-counties regarding life satisfaction, reported propensity to take risks, and average household size (Table 2.1). Regarding other characteristics, farming is the main economic activity for about 73% of our sample, many of whom finance farm activities from either own savings or income from the previous season. Many of the respondents tend to have a primary or secondary level education, and about 57% of the sample reported to have been directly affected by Covid-19.

Table 2.1: Summary of characteristics of our respondents

Variable	**Gender**			**Sub- county**			
	Total	Male (a)	Female (b)	Kathiani (a)	Machakos (b)	Mwala (c)	Yatta (d)
Age	51.3	54.0 **b**	49.3	51.8	52.1	52.4	49.3
Annual household expenditure (000 shillings)	149.7	172.4 **b**	133.7	144.9	172.1	143.0	141.9
Dietary diversity score	11.5	11.6	11.4	11.5	11.7	11.2	11.6
Household size	5	4.9	5.1	5.0 **b**	4.1	5.2 **b**	5.5 **b**
Asset count	6.6	7.0 **b**	6.3	6.2	6.2	6.6	7.2 **a b**
Risk aversion	0.5	0.5	0.6	0.6 **b**	0.4	0.5	0.5
Locus of control*	8.4	8.9 **b**	8	8.2	8.7	7.6	8.9
Life satisfaction score*	18.7	19	18.5	18.6	20.0 **a c d**	18.1	18.4
Propensity to take risks*	4.7	5.1 **b**	4.5	4.4	5.5 **a c d**	4.5	4.5

The letters show significance in statistical difference test of the means at 95% confidence interval.

*Locus of control, life satisfaction score, and reported propensity to take risks are constructs. The reliability of these constructs measured by the Cronbach's alpha values are 0.61, 0.52, and 0.21. The reliability measure for the propensity

to risks is very low owing to the small number of indicators we used. However, such a construct is considered relatively better compared to a single item.

Table 2.2: Farmer characteristics (categorical variables)

Variable			Gender		Sub-county			
		Total	Male	Female	Kathiani	Machakos	Mwala	Yatta
		N = 792	n = 327	n = 465	n = 187	n = 178	n = 193	n = 234
Occupation	Farming (crop/livestock)	73.2	79.8	68.6	77.0	75.8	69.9	70.9
	Employed (Informal)	8.5	7.3	9.2	3.2	9.0	11.4	9.8
	Employed (Formal sector)	6.4	5.8	6.9	6.4	4.5	8.8	6.0
	Business	11.4	6.7	14.6	12.3	9.6	9.8	13.2
	Student	0.3	0.3	0.2	-	1.1	-	-
	None	0.3	-	0.4	1.1	-	-	-
Education	Informal education	0.3	-	0.4	1.1	-	-	-
	No education	1.5	0.6	2.2	0.5	2.2	2.6	0.9
	Primary	43.8	35.5	49.7	34.8	42.7	40.9	54.3
	Secondary	39.8	46.5	35.1	48.7	37.1	40.9	33.8
	Vocational training	11.0	11.3	10.8	13.9	10.1	13.0	7.7
	University	3.7	6.1	1.9	1.1	7.9	2.6	3.4
Affected by Covid 19	Yes	57.3	57.2	57.4	68.4	37.1	56.5	64.5
Farming capital	Own savings	56.1	54.7	57.0	44.9	69.1	59.1	52.6
	Income from previous season	31.7	34.9	29.5	47.6	16.3	29.5	32.5
	Borrowing from friends	2.3	2.1	2.4	0.5	6.7	0.5	1.7
	Borrowing from bank	1.5	2.4	0.9	1.6	2.2	2.1	0.4
	Borrowing from MFI	2.1	2.8	1.7	1.6	2.8	2.1	2.1
	Remittances from family	2.3	0.3	3.7	3.2	1.1	2.6	2.1
	Table banking	1.5	0.6	2.2	-	1.7	2.1	2.1
	Livestock sales	2.5	2.1	2.8	0.5	-	2.1	6.4

2.5.5. Perceptions of risk attributes

The bulk of the questions were dedicated to assessing risk perceptions of the farmer. Assessing risk perceptions entailed asking farmers questions on several risk attributes for every risk in each domain. The risk attribute questions were asked only if the farmer mentioned to have experienced the risk. The risk attributes we focused on were historic and future return frequencies of the risk, severity of the risk, farmer's perceived ability to prevent the risk, the number of sources of the risk, the number of consequences caused by the risk, and whether the farmer did anything to adapt to the risk. Table 2.3 provides a summary of the risk attributes and how they were measured.

Table 2.3: Description of risk attributes and how they were measured

Variable	Description (how the question was asked)	Response
Historic frequency (frehisto*)	How many times has the risk occurred in the last 5 years (10 seasons)	Number ranging from 1 to 10
Future frequency (frefuture)	How many times is the risk likely to occur in the next 5 years	Number ranging from 1 to 10
Severity (severity)	On a scale of 1 to 5, where is not bad, and 5 is extremely bad, how could you rate this risk	5-point Likert
Sources	What are the main sources of the risk	Number
Consequences	What are the main consequences of the risk	Number
Ability to prevent (prevent)	On a scale of 1 to 5, where 1 is very able and 5 is not able at all, are you able to prevent (cope with) the risk from happening	5-point Likert
Adaptation (adaptation)	Did you do anything to reduce the impact of the risk	Yes/No

*The names in parenthesis are the short names we adopt for the risk attributes in the second part of the paper (model 1 and 2)

2.6. Measurement and analysis of risk perceptions

Measuring risk perceptions is as elusive as the concept of risk itself (Sjöberg, 2000). The diverse definitions of risk are associated with specific measurement strategies. However, even though there is no single unified measure of risk perception (van der Linden, 2017), most studies measure risk perception as a unidimensional multiplicative function of likelihood and severity (Wilson et al., 2019), with the assumption that individuals are objective when assessing risk. The studies use Likert scale items for the two variables, and data reduction through factor analysis or principal components analysis. Such a unidimensional view of risk perception can be limited on several accounts. The most important account is on how individuals make judgements under uncertainty as we discuss in our theoretical framework. Emotional and experiential assessment of risk through mental strategies such as the affect heuristic, availability heuristic, optimism, and unrealistic optimism tend to dominate over the objective, logical, and intellectual assessment (Epstein, 1994; Kahneman, 2011; Paek & Hove, 2017). Therefore, a measure considering probabilities and magnitude only is not reliable. The second account is on the interlinked nature of agricultural risks. Some of the risks have common sources and consequences, while some other risks cause or reinforce each other. The nomological network of the risks, sources and consequences may mask or amplify some risk attributes. Our estimation strategy extends the analysis beyond just probabilities and magnitude and considers the inter-connectedness of the risks we study. Though contexts are different, our estimation strategy is comparable to that of Wilson et al. (2019) who use confirmatory factor analysis to assess risk perception as a multidimensional construct. We use partial least squares path modelling for the reasons explained below.

PLS SEM is a variance-based multivariate analysis approach. Unlike the covariance based approach (CB-SEM) that seeks to increase covariance of the items of a common factor, PLS-SEM seeks to reduce unexplained variance of a construct using ordinary least squares as the estimation method (Hair et al., 2016). PLS-SEM is appropriate in our analysis because of the following reasons. First, our concept of risk entails a nomological network of risk attributes and risks in different domains. Second, we do not want to assume that our data achieves the requirements for other estimation approaches such as CB-SEM such as multivariate normality, and lastly, PLS-SEM supports estimation of formative constructs. Studies such as Burns et al. (1993) recommend the use of partial least squares in analysis of risk perceptions.

The PLS-SEM model is composed of a measurement (outer), and structural (inner) models. The measurement model is the interaction of manifest variables with the constructs that they explain. The structural model is the interaction between the various constructs.

2.6.1. Measurement model

Our measurement model consists of the risk attributes and the important risks. Though our manifest variables are the same (Table 2.3), based on our assumption described in previous sections, we consider the attributes for each risk as different variables. These attributes explain low crop yields, fluctuating input prices, and reduction in agricultural incomes, which are our formative lower-level constructs. Noteworthy is that only the manifest variables that have sufficient weights, and/or significant outer and inner loadings are included in the final model.

2.6.2. Structural model

The lower-level constructs interact to explain the overall risk perception which is our higher-level construct. The structural model is also formative in the sense that all the lower constructs point to the higher-level risk perception construct. Based on our findings from the risk

characterization, there is also some mediation among the constructs, i.e., some risks are sources of other risks. For example, fluctuations in input prices causes low crop yields, while low crop yield causes a reduction in agricultural incomes.

2.6.3. Estimation

We use SmartPLS 3 in the PLS SEM modelling. Our analysis focuses on 3 of the 6 most frequently cited problematic risks namely low crop yields, fluctuating input prices, and reduction in agricultural incomes, which represent the production, market, and financial domains. All the farmers included in this analysis have experienced all the risks in the past five years from the time of data collection, hence our sample reduces from 792 to 435. The objective of the path modelling is to determine the most important risk attribute(s) and the most important risk(s) as perceived by farmers. We use the weights from the measurement model as proxies for importance of risk attributes, and the path coefficients (structural model) as proxies for importance of the three risks in forming risk perceptions.

We consider two models in this analysis to represent two different perspectives of risk by the farmer (Figures 2.3 and 2.4). In model 1, we assume no interaction across risks (i.e., the farmer evaluates the risks in isolation),

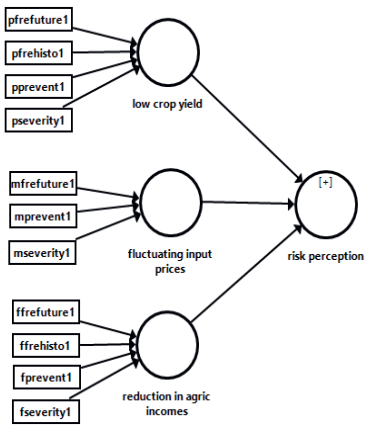


Figure 2.3: Model 1

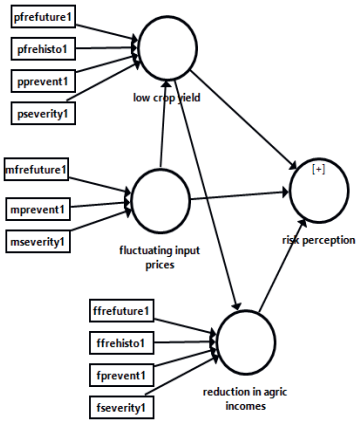


Figure 2.4: Model 2

while in the second model, we consider interactions. The interactions and their directions are informed by findings from the risk characterization in part one of the paper.

Based on findings from the characterization, low crop yields cause a reduction in agricultural incomes, and fluctuating input prices causes low crop yields. In this sense, fluctuating input prices cause a reduction in agricultural incomes through reduced crop yields as shown in Figure 3. Since model 2 is supported by theory, we use it to test whether there are differences in perceptions between men and women. We use the multiple group analysis (MGA) in SmartPLS to test for the differences.

Noteworthy is that before arriving at the models shown above, we first estimated models with all the risk attributes in Table 2.3. We use the results from the first step to eliminate risk attributes that do not significantly explain our risk perception composite according to the requirements for partial least squares path modelling (Hair et al., 2020). Manifest variables in the model should have outer weights greater than 0.7, otherwise be significant, or significant loadings,

or otherwise be at least 0.5 if not significant (Hair et al., 2019). Since we are estimating a formative model, focus is on the outer weights and collinearity among manifest variables. Collinearity among indicators should have a variance inflation factor (VIF) of less than 3[3]. The two models we estimate achieve all these criteria. Appendix item G provides the results from the test for collinearity.

We use a repeated indicator approach in the estimation. The repeated indicator approach is one of the two approaches used to model higher order composites. The approach has the advantage of considering the entire nomological network hence reducing loss of information compared to its counterpart two stage approach (Becker et al., 2012). Our PLS SEM algorithm entails a path weighting scheme. Though the available weighting schemes yield almost similar results, the path weighting scheme is recommended (Hair et al., 2016).

2.3.Results

2.3.1. Risk characterization: most problematic risk, main sources, and consequences

In this section, we provide results for the most problematic risks in each of the six domains (see Appendix Table 2.4).[4] Low crop yields, fluctuating input prices, reduction of agricultural incomes, sickness, price controls, and reduced number of meals were the most frequently mentioned problematic risks in production, market, financial, personal, institutional, and consumption domains. Table 2.4 provides a summary of the risks focusing on farmers' assessment of the risks' severity, ability to prevent (cope with) the risk, and why the risks were rated as most problematic. The figures represent percentages of the total number of farmers who experienced the respective risks.

[3] Important to note is that for formative models, model checks such as construct reliability, and average variance explained are not relevant (Hair et al., 2019).
[4] Important to note is that the most (least) frequently mentioned is not necessarily the most (least) problematic.

The results show that though most farmers are not at the extremes when it comes to rating the risks, more than half of those who experienced the risks rated the risks as severe, very severe, or extremely severe. More than half also reported that they were just able, unable, or extremely unable to prevent (cope with) the risks. Low crop yields was by far the most frequently mentioned production risk by farmers, and more than half of the farmers rated it as most problematic.

The results also show that consequences of a risk affecting most aspects of the farmer and those affecting all members of the household were the most frequently cited criteria for classifying a risk as most problematic.

Table 2.4: Summary of most problematic risks from each risk domain (percentage of farmers)

Risk Attribute/Risk	Low crop yield		Reduction in agricultural Incomes		Fluctuating input prices		Reduced number of meals		Price controls		Sickness	
	*M ** *n=307*	*F* *n=449*	*M* *n=241*	*F* *n=310*	*M* *n=153*	*F* *n=244*	*M* *n=127*	*F* *n=175*	*M* *n=13*	*F* *n=16*	*M* *n=121*	*F* *n=181*
Severity												
Not severe	4.6	4.5	4.6	5.2	4.6	2.9	7.1	4.6	15.4	12.5	6.6	1.1
Moderately severe	34.2	28.1	32.0	31.3	33.3	25.0	44.9	35.4	38.5	56.3	31.4	27.1
Severe	21.8	27.4	26.6	22.3	20.9	19.3	17.3	28.6	30.8	25	26.4	23.2
Very severe	24.8	29.2	22.4	28.1	22.9	32.8	20.5	22.9	15.4	-	26.4	37.6
Extremely severe	14.7	10.9	14.5	13.2	18.3	20.1	10.2	8.6	-	6.3	9.1	11
Perceived ability to prevent risk												
Very able	5.9	3.8	4.6	4.8	2.0	0.4	7.9	5.1	-	6.3	0.8	4.4
Moderately able	32.9	26.5	29.9	25.8	15.0	20.1	21.3	14.3	23.1	12.5	23.1	18.8
Able	23.8	23.6	24.5	20.0	13.1	8.2	28.3	30.9	23.1	-	19.8	23.2
Unable	29.0	30.7	27.8	34.5	34.6	41.0	32.3	36.6	23.1	75	30.6	29.3

Extremely unable	8.5	15.4	13.3	14.8	35.3	30.3	10.2	13.1	30.8	6.3	25.6	24.3
Why risk is most problematic												
Risk affects many aspects of life	33.3	26.3	48.6	40.0	33.0	26.3	15.2	17.4	39	24.7	57.9	53.9
The risk occurs more frequently	4.0	4.3	3.5	1.8	5.2	5.6	1	2.3	1.2	3.7	-	2.9
I lack sufficient coping	11.9	12.1	5.7	10.5	13.5	14.1	9.8	7.4	9.8	11.1	6.2	5.3
I have no control	6.1	5.2	6.4	3.7	13.5	15.4	2.5	2.7	18.3	33.3	4.1	5.3
Consequences are irreversible	4.0	6.7	0.4	0.5	0.3	0.2	-	-	1.2	2.5	2.1	4.4
Effects carry over many seasons	4.3	3.2	2.1	0.8	5.9	8.5	1	1.3	7.3	6.2	0.7	1.5
Affects all member of my household	33.0	37.6	33.0	41.6	25.3	27.6	70.6	68.8	22	16	25.5	24.8
Effects carry over the entire season	3.4	4.5	0.4	1.1	3.1	2.2	-	-	1.2	2.5	3.4	1.9

*M and F stand for male and female respectively.

Regarding risk sources, weather related shocks, pests and diseases are the main causes of low crop yields. Drought was the most frequently mentioned source (about 79% of all the farmers who experienced low crop yields) (Figure 2.5). The most frequently mentioned consequences of low crop yields were reduced availability of food (78% of the farmers), and reduction of agricultural incomes (63% of the farmers). Regarding market risks, the most frequently mentioned cause of fluctuations in input prices was high demand and low supply in the market. Consequently, about 64% of the farmers who experienced fluctuations in input prices mentioned that they used traditional inputs as a result. Noteworthy is that for the case of market risks, fluctuating input prices was selected as the most problematic even though fluctuations in output prices was the most frequently mentioned market problem.

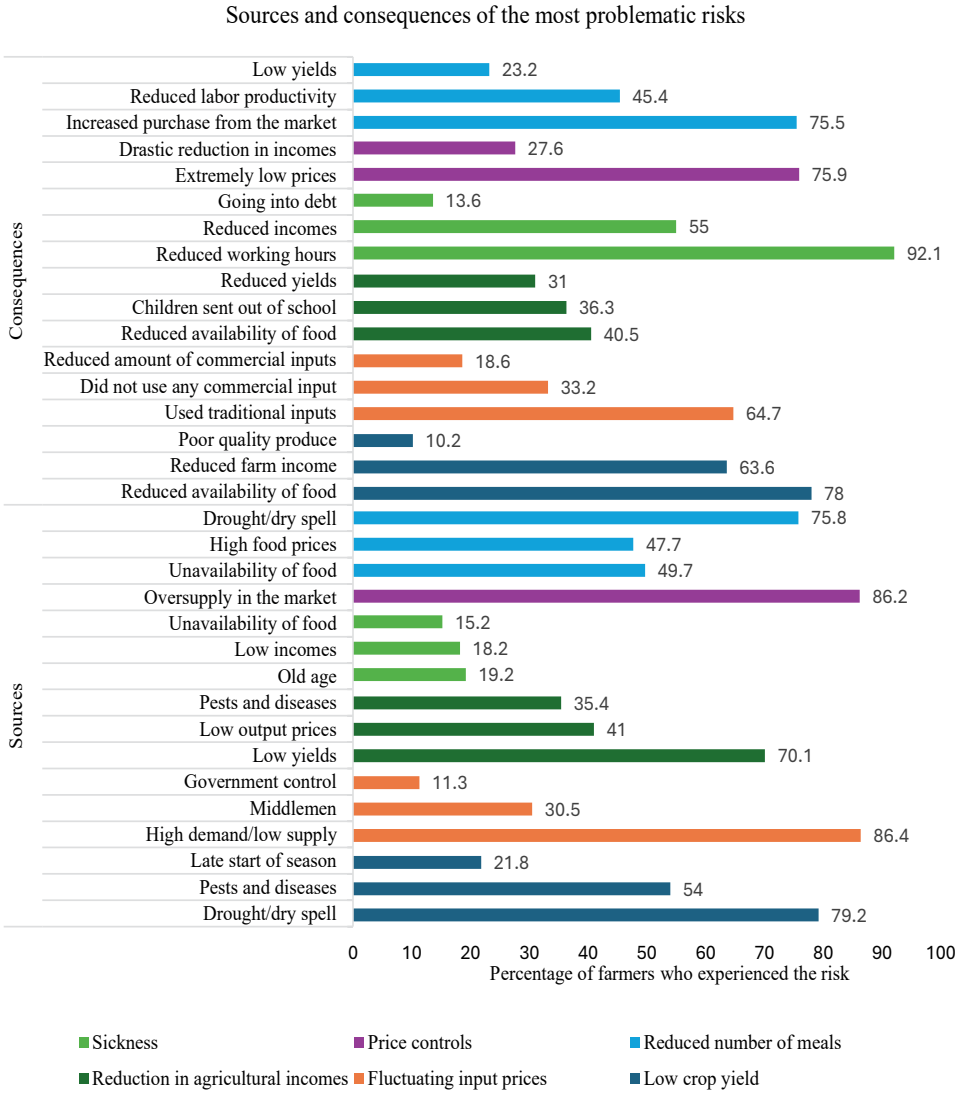


Figure 2.5: Sources and consequences of the problematic risks

For the case of reductions in agricultural incomes, low yields, low output prices, and pests and diseases were the main sources. The most frequently mentioned (70% of the farmers) was low crop yields. Reduced availability of food, children sent out of school, and low crop yields were identified as the main consequences of reduction in agricultural incomes. Regarding sickness, old age, low incomes, and unavailability of food were identified as the main causes. The main

consequences of sickness were reduced working hours, reduced incomes, and going into debt. In this regard, a shock in incomes is likely to have a double effect on households that are experiencing sickness.

Regarding institutional risks, price controls (or lack of it) was the most problematic. The risk applies mostly to output prices since oversupply in the market was identified as the main cause. Consequently, farmers end up selling at extremely low prices. Lastly, regarding reduced number of meals, drought/dry spell, unavailability of food, and high food prices were identified as the main sources, while increased purchases from the market, reduced labor productivity, and low crop yields were identified as the main consequences.

A critical evaluation of the risks, main sources and consequences shows how interconnected the risks, risk sources, and consequences are. For example, drought directly causes low crop yields, and reduced number of meals indirectly. Low crop yields result in a reduction in agricultural incomes that in turn cause a reduction in availability of food. Reduced availability of food (reduced number of meals) in turn is among the main causes of sickness and low crop yields. Sickness in turn causes a reduction in agricultural incomes. The cycle continues. It therefore becomes evident that though we only consider a limited number of risks, tracing the whole cycle of risks, their sources, and consequences is a non-trivial task that presents a "chicken" and "egg" situation. Such a complex interconnection of risks, risk sources and consequences requires a bundle of risk management strategies to effectively manage the risks.

2.4. *Determination of important risk attributes through partial least squares path modelling*

We now turn to determining the most important risk attributes and risk (hypothesis 2). The results from the path modelling show no difference between model 1 and model 2 (Table 2.5). All the indicators included significantly explain both the lower and higher constructs at 1% albeit with

weak associations (i.e., the weights are less than 0.3). Both models show that perceived ability to prevent a risk from happening or cope with it, and its severity have the strongest effect on perception of the three risks, and the overall risk perception. However, notwithstanding the similarities in the outer weights, there are differences in path coefficients for the two models as shown in Table 2.6. For model 1, the path coefficients for the three risks are comparable, with reduction in agricultural incomes having a slightly greater contribution to the overall risk perception. Model 2 on the other hand shows that low crop yields and fluctuating input prices have bigger total effects following the direct and indirect effects on the overall risk perception.

Table 2.5: Outer weights for models 1 and 2

	Fluctuating input prices		Low crop yield		Reduction in agricultural incomes		Risk perception	
Attribute	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
ffrefuture1					0.256	0.250	0.142	0.139
ffrehisto1					0.258	0.222	0.139	0.132
fprevent1					0.543	0.574	0.212	0.219
fseverity1					0.445	0.443	0.185	0.185
mfrefuture1	0.340	0.309					0.110	0.107
mprevent1	0.580	0.605					0.198	0.205
mseverity1	0.483	0.475					0.182	0.183
pfrefuture1			0.326	0.294			0.152	0.144
pfrehisto1			0.269	0.213			0.146	0.137
pprevent1			0.611	0.673			0.216	0.223
pseverity1			0.314	0.317			0.127	0.127

Note: All the indicators are significant at 1% on both the lower and higher constructs.

The f, m, and p prefixes before the risk attributes denote the domain of the risk namely financial, market, and production respectively.

Table 2.6: Path coefficients and their significance

Construct	Mean		P Values	
	Model 1	Model 2	Model 1	Model 2
Fluctuating input prices	0.335	0.664	0.000	0.000
Fluctuating input prices -> Low crop yields*		0.488		0.000
Low crop yield	0.420	0.668	0.000	0.000
Low crop yields -> Reduction in agricultural incomes*		0.580		0.000
Reduction in agricultural incomes	0.446	0.447	0.000	0.000

*This denotes the effect of one of the lower constructs on another lower construct.

2.5. Determination of differences in perceptions between men and women

Lastly, we address the third hypothesis by testing for differences in perceptions of both the weights of risk attributes and path coefficients between men and women. This test is motivated by the statistically significant differences we found in some of the variables likely to influence risk perceptions highlighted in Table 2.1. We find that men tend to give larger weight for historic frequencies for the case of reduction in agricultural incomes, while women tend to have a greater weight on perceived ability to prevent reduction in agricultural incomes (Table 2.7). These differences between the two groups are statistically significant at 5%. We also find a significant difference at 10% in the weights for historic probabilities for the case of low crop yields. Like reduction in agricultural incomes, men tend to have on average a bigger weight. Table 2.8 provides more details on these findings. We do not find any significant statistical difference in the path coefficients for both groups. However, we find a significant difference at 5% in the total effects of fluctuating input prices on the overall risk perception. Women tend to have bigger weights on average compared to men (Table 2.8).

Table 2.7: Lower construct perception differences between men and women

Risk attribute	Reduction in agricultural incomes		Fluctuating input prices		Low crop yields	
	Outer Weights (Female - Male)	p-Value	Outer Weights (Female - Male)	p-Value	Outer Weights (Female - Male)	p-Value
ffrefuture1	-0.078	0.527				
ffrehisto1	-0.226	0.041**				
fprevent1	0.261	0.025**				
fseverity1	-0.053	0.639				
mfrefuture1			-0.185	0.217		
mprevent1			0.154	0.303		
mseverity1			-0.147	0.333		
pfrefuture1					0.21	0.131
pfrehisto1					-0.229	0.073*
pprevent1					0.092	0.417
pseverity1					-0.061	0.637

**, * denote significance at 5% and 10% respectively.

Table 2.8: Test for differences across path coefficients (total effects) between men and women

Risk perceptions	Total Effects-diff (Female - Male)	p-Value
Fluctuating input prices -> Low crop yield	0.12	0.101
Fluctuating input prices -> Reduction in agricultural incomes	0.056	0.392
Fluctuating input prices -> Risk perception	0.127	0.03**

Low crop yield -> Reduction in agricultural incomes	-0.031	0.642
Low crop yield -> Risk perception	-0.079	0.123
Reduction in agricultural incomes -> Risk perception	-0.051	0.282

3. Discussion & implications

Our risk analysis entails characterization of agricultural risks, determination of risk attributes that matter in forming a small-holder farmer's risk perception, and testing whether there are differences in the perceptions between men and women. Results from the risk characterization show that indeed small-holder farmers face many important risks across the different risk domains as it has been highlighted in many studies already. Low crop yield is the most frequent (in terms of mentions) risk among the farmers and is the most problematic in the production domain. Fluctuating input prices, reduction in agricultural incomes, price controls (and lack of price controls), reduced number of meals, and sickness are the most problematic in the market, financial, institutional, consumption and personal risk domains. We find that risks that affect many aspects of the farmer's life as an individual, and those that affect many household members are deemed the most problematic. Return frequencies of the risks had the least mentions by farmers as the main criterion for ranking a risk as most problematic. These two findings point to the possibility of dominance of the affect heuristic in risk assessment among farmers. Intuitively, farmers are more likely to adopt risk management strategies for risks that most invoke affect.

We also identify main sources and main consequences of the risks in the characterization. We find that other than sources such as climate related shocks like drought and dry spells, farmers know that some risks cause other risks. For example, farmers are aware of the role of low crop yields in reducing agricultural incomes as well as the role of fluctuating input prices on low yields and ultimately low incomes. This is an interesting finding since from it, we can infer the pathways

for adaptation and risk management that the farmer thinks are relevant to her. These results provide further empirical evidence on the importance of multiple risks assessment in the context of small-scale farmers as pointed out by Komarek et al. (2020) and Ansah et al. (2020). The need to assess multiple risks in agriculture is also elaborate when we compare models 1 and 2. From the comparison, we find that considering the links from one risk to another shifts importance of various risks as perceived by the farmer. We find that independently, reduction of agricultural incomes has a relatively bigger contribution to forming farmers' risk perceptions. However, model 2 shows that low crop yields and fluctuating input prices tend to be more important when we consider total effects.

Analysis of risk attributes and their importance in forming risk perceptions shows that first, both historic and future probabilities of risks, perceived ability to prevent a risk, and severity of the risk significantly influence a farmer's risk perception. Though our findings are in tandem with theory and literature when it comes to probabilities and severity of a risk (Sullivan-Wiley & Short Gianotti, 2017; van Duinen et al., 2015), we find that perceived ability to prevent (cope with) the risk matters the most to the farmer's perceptions. Wilson et al. (2019) also found probabilities to be less critical in the way individuals assess risks. Consequently, in the context of small-scale farmers, risk management mechanisms should focus on risks for which the farmer has dismal control over, or ability to cope with them. However, of importance is also filtering for the acceptable levels of various risks by the farmer when considering ability to prevent risks. High acceptance of (tolerance to) risk may give a false impression of high ability to prevent the risk (cope with it) to the detriment of keeping farmers in risk induced poverty traps (Azariadis & Stachurski, 2005).

Second, the data supports our initial hypothesis that risk attributes such as return frequencies that may be considered objective can be interpreted differently by farmers in the same geographical location with almost similar "objective" exposure to the risks. Interpretations of the attributes depend on the risk and the individual. Such high heterogeneity in perceptions calls for more targeted risk management strategies.

Further analysis of the risk attributes shows that the four risk attributes consistently and significantly influence perceptions for low crop yields and reduction in agricultural incomes. However, historic probabilities tend to matter less for the case of fluctuating input prices. Therefore, our data does not support the notion that a certain set of risk attributes can generalize the concept of risk across many risks.

Third, we do not find major differences in the risk perceptions between men and women except for the effect of perceived ability to prevent (cope with) risks and historic probabilities for the case of reduction in agricultural incomes. Both the similarities and differences are justifiable as discussed by (Gustafson, 1998). On one hand, the similarities may be attributed to the fact that perception in our case involved assessment of the attributes of a risk, which involves personal biases to a lesser extent compared to assessment of self with respect to the risk as in the case of ability to prevent or cope with the risk, which involves to a larger extent personal biases, and emotions (Slovic et al., 2012). Individuals then may tend to care more about risk attributes that cause them to evaluate self with respect to the risk than those that do not. On the other hand, the significant difference in perceived ability to control (cope with) a risk between men and women is plausible following the differences we find in wealth status namely annual expenditure and asset count, locus of control, and propensity to take risks, where scores for men tend to be significantly

higher than those for women. Poor scores especially in terms of wealth status among women may also mean more exposure to risk relative to men.

3.3. Limitations of the study

The contribution of our study to the knowledge on risk perceptions among small scale farmers is evident. However, we need to point out some limitations of this study. First, we consider the entire farm enterprise making our scope wide instead of focusing on a particular enterprise, crop, or livestock. Notwithstanding, studies with a wide scope as this one are useful in informing more focused studies. We highly recommend the use of the approach we have used for specific farm enterprises. Second, our analysis considers risk attributes only, and implicitly assume the role of individual attributes. Though several studies have already identified the socio-economic and demographic factors that influence risk perceptions (Dosman et al., 2001; Ullah et al., 2015), none has used the approach we use. Future research can explore measuring individual attributes as constructs rather than single items and estimate a single model with both risk and individual attributes. Third, though we started with a sample size of 792, we only consider 435 farmers and three risks in the empirical assessment. We lose data along the way in our analysis. The framing of the questions could not allow us to use the entire sample size. Future research should consider a large sample of farmers and a wide range of risks and risk attributes. Lastly, there is a likelihood that the attributes of the risks are also linked to each other, in the sense that the ability to prevent for instance low crop yield is linked with the ability to prevent fluctuations in input prices or reduction of agricultural incomes. Future research should also consider this interconnectedness of the risk attributes.

4. Conclusion

We have characterized agricultural risks and identified the most problematic risk, the main sources of the most problematic risks, their consequences, and why farmers perceive the risks as the most problematic. Low crop yields, fluctuating input prices, reduction in agricultural incomes, reduced number of meals, price controls and sickness are the most problematic. Low crop yields is the most frequent of them all in terms of mentions. The main sources are weather related (drought/dry spell and late start of season), and pests and diseases. The sources and risks are interlinked in that the risks have common sources, and that some risks cause each other. Therefore, risk management tools should aim to address multiple sources such as weather-related shocks and other connected risks. Bundling risk management strategies for example agricultural insurance with agricultural inputs can enable farmers to manage many relevant risks simultaneously. The bundling might also improve the uptake of agricultural insurance that is currently low.

We have also analyzed risk perception as a hierarchical multi-dimensional construct that starts from risk attributes to the risks and risk domain instead of a factor analysis as conventionally done. The data supports this conceptualization. Though we find that both historic and future return frequencies (probabilities), severity and ability to prevent a risk or cope with it matter in forming farmers' risk perceptions, ability to prevent tends to be the most important. Future work on risk management for small scale farmers should consider this attribute. However, it may be important to first determine whether the farmer considers her ability to prevent or cope with a risk, and the other risk attributes in making decisions, or whether other factors such as emotions override the importance of the risk attributes as discussed by Loewenstein et al. (2001).

We have also established that considering agricultural risks independently neglecting the inter-connectedness of the risks may misguide understanding of the risks that matter to the farmer.

We find that though reduction in agricultural incomes is relatively more important when considered independently, fluctuating input prices and low crop yields tend to be more important in forming perceptions of the farmer when the inter-connectedness of the risks is considered. Future exploration of the potential of keeping input prices low for instance through subsidies, and/or agricultural insurance on increasing crop yields is pertinent. However, approaches considering subsidies should also consider continuity of the use of the inputs once the subsidies phase out.

Lastly, we do not find major differences in the perceptions of the risk attributes and the linkages across risks between men and women. However, we find a significant difference when it comes to perceived ability to control or cope with a risk. We attribute this difference to wealth status, locus of control, and reported propensity to take risks. As such, disparities in access to resources between men and women might be an important issue to consider when designing risk management tools that target women.

Appendix 2

Appendix 2.1: Questions

Appendix 2.1: Indicators of locus of control

These questions are based on a 5-point scale from strongly disagree (1) to strongly agree (5) (1=Strongly agree; 2=Agree; 3=Not sure; 4=Disagree; 5=Strongly disagree). Select one for each of the questions.

Internal items (self-drive, motivation, belief that we can change our circumstances)

1. When I make plans, I am almost certain that I can make them work
2. What happens to me is my own doing
3. Getting people to do the right things depends on ability; luck has nothing to do with it
4. When I work hard, I get rewards
5. I have the needed knowledge and skills to make my life better
6. If I plan myself well, I can avoid many unpleasant outcomes, now and in the future

External Items (wellbeing is controlled by some strong other)

7. Many of the unhappy things in people's lives are partly due to bad luck
8. Getting a good job depends on mainly on being in the right place at the right time
9. Many times, I feel that I have little influence over the things that happen to me
10. Whatever you do, if things are to go wrong, they will go wrong
11. The yields I get from agriculture at the end of the season are beyond my control

Appendix 2.2: Indicators of general satisfaction with life

Indicate for each of the following questions whether you: 1=Strongly agree; 2=Agree; 3=Not sure; 4=Disagree; 5=Strongly disagree

1. I am satisfied with my life
2. I have achieved all the goals/dreams I wanted to achieve in life
3. I am working to my best to see that I improve the quality of my life
4. I am satisfied with my social relations (including my family)
5. I am satisfied with the material things that I have now

6. Every morning, I look forward to a good day ahead
7. I have suffered a lot in this life
8. I live a life of poverty
9. I have access to nutritious food

Appendix 2.3: Reported propensity to take risks

1. How likely are you to take risks (1=very likely; 2=likely; 3=Not sure; 4=unlikely; 5=very unlikely)
2. How likely can (do) you adopt new agricultural technologies that you have never used before (1=very likely; 2=likely; 3=Not sure; 4=unlikely; 5=very unlikely)
3. I like learning about something, see results from other people, before I can try that thing (1=Strongly agree; 2=Agree; 3=Not sure; 4=Disagree; 5=Strongly disagree)

Appendix 2.4: Risk game as adopted from Tanaka et al. (2014)

Instructions

We are going to play a game that involves money. Your earnings will depend partly on your choice and partly on chance. There are 3 series of questions. Series 1 consists of 14 questions, series 2 consists of 14 questions, and series 3 consists of 7 questions. In total, we have 35 questions. We will offer you two plans; plan A and plan B. You are required to choose a plan for each of the questions. Once you finish answering the questions, we will offer you a bag containing 35 balls with numbers 1 to 35. You are required to select a ball from the bag. We will then play the selected question for real money. For example, if you choose ball number 10, we will play question number 10 for real money.

Series 1 **Series 2**

Appendix Table 2.1: Payouts in the risk game

Option A		
#	Balls 1 - 3	Balls 4 - 10
1	120	30

Option B		
#	Ball 1	Balls 4 - 10
1	204	15

Option A		
#	Balls 1 - 9	Ball 10
1	120	90

Option B		
#	Balls 1-7	Balls 8 - 10
1	162	15

2	120	30
3	120	30
4	120	30
5	120	30
6	120	30
7	120	30
8	120	30
9	120	30
10	120	30
11	120	30
12	120	30
13	120	30
14	120	30

2	225	15
3	249	15
4	279	15
5	318	15
6	375	15
7	450	15
8	555	15
9	660	15
10	900	15
11	1200	15
12	1800	15
13	3000	15
14	5100	15

2	120	90
3	120	90
4	120	90
5	120	90
6	120	90
7	120	90
8	120	90
9	120	90
10	120	90
11	120	90
12	120	90
13	120	90
14	120	90

2	168	15
3	174	15
4	180	15
5	186	15
6	195	15
7	204	15
8	216	15
9	231	15
10	249	15
11	270	15
12	300	15
13	330	15
14	390	15

Estimates of risk aversion (σ) and probability weights (α)

Appendix Table 2.2: Estimates of risk aversion and probability weights

σ	Switching question in Series 1														
Series 2	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**Never**
1	1.50	1.40	1.35	1.25	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.65	0.55	0.50
2	1.40	1.30	1.25	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.60	0.55	0.50
3	1.30	1.20	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.55	0.50	0.45
4	1.20	1.15	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.50	0.45	0.40
5	1.15	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.40	0.35
6	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35
7	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30
8	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25
9	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20
10	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20
11	0.80	0.70	0.65	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.15
12	0.75	0.65	0.60	0.55	0.50	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20	0.15	0.10
13	0.65	0.60	0.55	0.50	0.45	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.15	0.10	0.10
14	0.60	0.55	0.50	0.45	0.40	0.35	0.35	0.30	0.25	0.20	0.15	0.10	0.10	0.10	0.05
Never	0.50	0.45	0.40	0.40	0.35	0.30	0.30	0.25	0.20	0.15	0.10	0.10	0.05	0.05	0.05

α	Switching question in Series 1														
Series 2	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**Never**

1	0.60	0.75	0.75	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30	1.40	1.45
2	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.35	1.40
3	0.55	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30
4	0.50	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25
5	0.45	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20
6	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15
7	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10
8	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05
9	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00
10	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95
11	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
12	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85
13	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80
14	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75
Never	0.05		0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.45	0.55	0.55	0.65	0.60

Appendix 2.5: Risks experienced by farmers (percentages)

Appendix Table 2.3: Risks experienced by farmers

Domain	Risk	Total	Gender		Sub county			
		N=792	Male n=327	Female n=465	Kathiani n=187	Machakos n=178	Mwala n=193	Yatta n=234
Production	Low crop yields	95.3	93.6	96.6	95.2	93.8	93.8	97.9
	Death of livestock	47.7	42.5	51.4	44.4	49.4	41.5	54.3
	Lack of fertilizer	28.0	26.9	28.8	40.6	16.9	26.4	27.8
	Post-harvest loss	24.5	22.0	26.2	24.6	16.3	23.8	31.2
	Reseeding/replanting	23.1	20.5	24.9	17.1	33.1	24.9	18.8
	Poor germination	22.0	19.6	23.7	15.5	24.2	20.7	26.5
	Lack of water	18.1	22.0	15.3	10.2	30.3	10.9	20.9
	Low animal production	13.4	16.2	11.4	7.0	16.9	13.5	15.8
	Poor quality produce	10.4	11.9	9.2	11.2	19.1	5.2	7.3
	Pests and diseases	4.2	3.7	4.5	1.1	-	2.1	11.5
	Equipment breakdown	3.9	4.3	3.7	0.5	11.8	1.0	3.0
	Lack of seeds	0.8	0.6	0.9	1.6	-	0.5	0.9
Financial	Reduction in agricultural incomes	69.6	13.1	10.3	15.5	9.6	12.4	9.0

	Reduction in daily wages	15.7	2.8	2.6	3.2	2.2	4.1	1.3
	Inability to replay loan	11.5	-	0.9	-	1.1	0.5	0.4
	Increase in interest rates	2.7	15.6	15.7	14.4	7.3	16.1	22.6
	Reduction in non-agricultural income	0.5	73.7	66.7	75.9	62.9	70.5	68.8
Market	Fluctuating output prices	72.9	75.5	71.0	78.1	57.3	79.8	74.8
	Fluctuating input prices	50.1	46.8	52.5	50.3	50.0	48.7	51.3
	Fluctuating interest rates	1.1	0.9	1.3	-	1.1	3.1	0.4
	Lack of markets	1.1	0.9	1.3	1.1	-	2.1	1.3
Consumption	Reduced quantities of food	38.1	38.8	37.6	38.0	39.9	37.8	37.2
	Reduced number of meals	33.7	33.9	33.5	31.0	43.3	36.8	26.1
	Lack of a balanced diet	21.5	23.5	20.0	20.3	16.3	25.9	22.6
	Food contamination	3.2	3.1	3.2	4.3	3.4	4.1	1.3
	Food lacking necessary nutrients	2.5	3.4	1.9	2.1	5.6	1.6	1.3
Institutional	Importation of cheaper produce	11.1	12.5	10.1	8.6	19.7	10.9	6.8
	Price controls	3.7	4.0	3.4	0.5	12.4	1.0	1.7
	Tenure security	3.4	4.9	2.4	3.7	7.9	1.6	1.3
	Covid related restrictions	1.5	1.5	1.5	1.1	1.1	1.6	2.1
	High export tariff	0.9	2.1	-	2.7	-	-	0.9
	Breach of contract farming agreement	0.4	0.6	0.2	1.1	-	-	0.4
	Lack of price control	0.3	0.6	-	0.5	-	0.5	-
Personal	Sickness	38.1	37.0	38.9	36.4	42.7	38.9	35.5
	Traffic accident	4.8	6.4	3.7	5.9	4.5	2.6	6.0
	Divorce	1.3	1.2	1.3	0.5	2.8	1.0	0.9
	Death of family member	0.4	-	0.6	0.5	0.6	-	0.4
	Land disputes	0.6	-	1.1	1.1	0.6	0.5	0.4
	Other accidents	0.4	0.6	0.2	0.5	1.1	-	-
	Domestic conflicts	0.1	-	0.2	-	0.6	-	-

Appendix Table 2.4: Most problematic risks

Domain	Risk	Gender			Sub-county			
		Total	Male	Female	Kathiani	Machakos	Mwala	Yatta
Production	Low crop production	56.5	56.3	56.6	57.2	56.3	58.0	54.7
	Low animal production	16.8	18.0	16.0	16.6	18.2	19.7	13.7
	Reseeding/replanting	13.7	13.5	13.8	16.6	10.2	14.0	13.7
	Equipment breakdown	5.3	5.5	5.2	3.7	6.3	3.6	7.3
	Poor germination	4.1	2.8	5.0	3.7	4.5	1.6	6.0
	Death of livestock	2.0	2.4	1.7	0.5	2.8	2.1	2.6
	Post-harvest loss	0.6	0.3	0.9	0.5	1.1	-	0.9
	Lack of seeds	0.4	0.3	0.4	-	-	0.5	0.9
	Pest and diseases	0.3	0.6	-	0.5	-	0.5	-
	Poor quality produce	0.3	0.3	0.2	0.5	0.6	-	-
	Lack of water	0.1	-	0.2	-	-	-	0.4
Financial	Reduction in agricultural incomes	93.2	93.6	92.9	95.8	93.1	90.8	93.1
	Increase in interest rates	5.7	6.0	5.5	2.4	5.4	8.6	6.4
	Inability to repay loan	0.5	0.4	0.5	1.8	-	-	-
	Reduction in non-agricultural incomes	0.6	-	1.1	-	1.5	0.6	0.5
Market	Fluctuating input prices	71.1	72.6	70.0	72.3	80.1	66.7	67.6
	Fluctuating output prices	27.8	26.7	28.5	27.2	19.9	31.0	31.0
	Lack of markets	1.1	0.7	1.5	0.6	-	2.3	1.4
Consumption	Reduced number of meals	79.4	76.4	81.5	74.8	80.2	76.6	85.0
	Reduced quantities of food	14.4	16.3	13.1	17.4	14.4	15.6	10.9
	Food contamination	5.6	6.4	5.0	6.1	5.4	7.0	4.1
	Food lacking necessary nutrients	0.6	1.0	0.3	1.7	-	0.8	-
Institutional	Price controls	87.7	86.6	88.9	81.8	91.4	86.7	86.7
	Covid related restrictions	5.5	4.9	6.2	6.1	2.9	10.0	6.7
	High export tariff	3.1	3.7	2.5	3.0	4.3	3.3	-

Breach of contract farming agreement	1.8	2.4	1.2	6.1	-	-	3.3
Cheap imports	0.6	1.2	-	-	1.4	-	-
Tenure security	0.6	-	1.2	-	-	-	3.3
Lack of price control	0.6	1.2	-	3.0	-	-	-

Appendix 2.6: Tests

Appendix Table 2.5: Collinearity test

Variable	VIF
ffrefuture1	1.342
ffrefuture1	1.478
ffrehisto1	1.339
ffrehisto1	1.473
fprevent1	1.112
fprevent1	1.666
fseverity1	1.111
fseverity1	1.42
mfrefuture1	1.026
mfrefuture1	1.151
mprevent1	1.195
mprevent1	1.572
mseverity1	1.213
mseverity1	1.387
pfrefuture1	1.382
pfrefuture1	1.509
pfrehisto1	1.393
pfrehisto1	1.508
pprevent1	1.085
pprevent1	1.502

pseverity1	1.043
pseverity1	1.236

Appendix Table 2.6: Correlation of risk perceptions and farmer characteristics

		1	2	3	4	5	6	7	8
1	Risk aversion	-							
2	Dietary diversity	-0.088	-						
3	Locus of control	-0.066	0.012	-					
4	Age	-0.038	-0.054	0.007	-				
5	Life satisfaction	-0.075	-0.022	0.373***	0.136**	-			
6	Asset count	-0.083	0.326***	-0.007	0.048	0.074	-		
7	**Risk perception**	**-0.139****	**-0.03**	**0.015**	**0.088**	**-0.081**	**-0.108***	**-**	
8	Annual expenditure	-0.068	0.197***	-0.071	0.046	0.057	0.289***	-0.08	-

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix 2.7: Regression analysis of effect of variables of interest on risk perceptions

Model diagnostics show that the assumptions for OLS (no multicollinearity, homoscedasticity, normality of the residuals) are achieved by the data.

Appendix Table 2.7: Factors affecting risk perceptions

Dependent variable:	Risk perception
Risk aversion	-0.313***
	(0.101)
Dietary diversity	0.005
	(0.025)
Age	0.006
	(0.004)
Life satisfaction	-0.024**
	(0.01)

Locus of control	0.008
	(0.009)
Asset count	-0.025
	(0.016)
factor (Education)2	0.701
	(1.049)
factor (Education)3	0.344
	(0.983)
factor (Education)4	0.037
	(0.984)
factor (Education)5	0.301
	(0.993)
factor (Education)6	-0.112
	(1.015)
factor (Occupation)2	0.02
	(0.205)
factor (Occupation)3	-0.134
	(0.212)
factor (Occupation)4	-0.103
	(0.158)
factor (Occupation)6	-0.739
	(0.982)
Constant	0.149
	(1.08)
Observations	435
R2	0.084
Adjusted R2	0.051
Residual Std. Error	0.975 (df = 419)
F Statistic	2.569*** (df = 15; 419)

Note: *p<0.1; **p<0.05; ***p<0.01. Figures in brackets are standard errors

Chapter 3

Are dairy farmers willing to pay for improved forage varieties? Experimental evidence from Kenya

Abstract

This chapter is based on an experiment that sought to assess dairy farmers' willingness to pay (WTP) for different improved forage varieties and two types of dried feed in Meru County, Kenya. WTP was elicited using the Becker-DeGroot-Marschak (BDM) mechanism and the data was analyzed using a mixed-effects model. Results show that WTP for most forage products was below the market prices, and that WTP differed significantly between cooperative and non-cooperative farmers. WTP was not statistically different for related varieties on average. Factors such as prior exposure to the forages, farm size, whether a farmer practiced zero-grazing, and livestock ownership positively influenced. Age and monthly income were negatively associated with WTP. The below market price WTP underscore the need for strategies that can lower the costs of the forages such as reducing production, certification, storage, and transportation expenses. The positive effect on WTP of prior exposure suggests that opportunities for farmers to experiment with forages, combined with targeted promotions and information campaigns on the benefits of improved traits, could substantially increase demand for improved forage products.

Key words: Improved varieties; Willingness to pay; Forages; Cooperatives; Livestock

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3.1. Introduction

Livestock play an important role in enhancing both food and nutrition security in developing countries (Herrero et al., 2013; Randolph et al., 2007). However, poor access to quality feed undermines this important role (Balehegn et al., 2020). Improved forage varieties bear the potential to supply high quality feed for livestock and optimize livestock nutrition and production (Fuglie et al., 2021). The improved varieties also have other advantages especially in reducing greenhouse gas emissions and improving the quality of soils when integrated with food crops (Paul et al., 2020). Unfortunately, demand for the improved forage seeds is low (Morrison et al., 2023), mostly because livestock farmers in developing countries either depend on rain-fed natural pastures, or conventional forages such as Napier grass or maize stalks (Creemers & Aranguiz, 2019), which are usually of low quality. Feed conservation (either as hay or silage), which can offset feed deficits during dry seasons when the quantities (quality) of natural pastures are (is) low is limited amongst livestock farmers mainly because of lack of capacity and unsuitability of some of the conventional forages for conservation (Balehegn et al., 2022). Low utilization of the improved varieties results in low forage productivity. Consequently, livestock farmers continue to experience frequent feed shortages, and low livestock productivity. Feed shortages and low productivity threaten the livelihoods and food security of millions who directly depend on livestock and put more pressure on the environment.

Some aspects of the low utilization and demand for the improved varieties can be explained by factors that hinder adoption of other agricultural technologies such as lack of awareness about the technologies, liquidity constraints, and uncertainty about yield distributions highlighted in Magruder (2018). However, some challenges might be unique to forages. For example, some farmers may consider forage production to be inferior to the production of other cash and food

crops hence the preference to produce other crops such as maize to meet consumption needs. Second, most of the grasses are perennial implying that farmers do not need seeds seasonally (Mwendia et al., 2016). Third, though a lot of effort goes to the breeding of improved forage varieties, the enhanced agronomic traits may not reflect the priorities of the farmers as far as livestock feed is concerned. Unlike other crops such as maize for which several assessments on trait preference have been conducted (see for example Kassie et al., 2017; Lybbert, 2006; Mastenbroek et al., 2021), little has been done on assessing trait preference for improved forage seeds, implying that there is little evidence in the literature on whether livestock farmers consider the agronomic traits when making decisions on the forages to produce or to feed their livestock on, and whether there are traits (and varieties) for which livestock farmers are willing to pay a premium.

The aim of this study is to fill the knowledge gap on the low demand for improved forage varieties by dairy farmers. We assess demand by eliciting dairy farmers' willingness to pay (WTP) for four seed varieties and two types of dried feed in Meru County, one of the 45 agricultural counties of Kenya. A large portion of the county (mostly Imenti, Buuri, and Tigania) is well suited for both crop and livestock production. Meru County has about 180, 000 dairy cows and about 250,000 beef cattle (Meru Dairy Cooperative Union, 2018). Milk production is about 7 liters/cow/day, which is below that of other counties such as Kiambu County which is at 12 liters/cow/day (Tegemeo & Kenya Dairy Board, 2021). One of the main challenges to dairy production in the county is poor animal nutrition (Meru Dairy Cooperative Union, 2018), which is partly caused by poor access to high quality feed especially during the dry season.

The four seed varieties we consider are *Brachiaria Mulato 2*, *Brachiaria Cayman*, *Brachiaria Cobra*, and *Panicum cv. Mombasa*. The Brachiaria varieties were registered in Kenya

in 2016, while the Panicum variety was registered in Kenya in 2021. The Brachiaria varieties are obtained through breeding, while the Panicum variety is a selection. Because there was no hay from the Brachiaria or Panicum varieties in the market by the time we conducted the study, we considered rice straws (which we dub "ordinary hay") and Boma Rhodes hay to represent inferior and superior types of dried feed respectively. Consideration of both seeds and dried feed helps us to generate evidence for two products at different stages of the value chain—demand for one can either suppress or increase demand for the other—an important determinant of commercialization. For example, Mwendia et al. (2016) notes that a high demand for dried feeds can offset demand for seeds even though the grasses are perennial, and that demand for either the seeds or dried feeds must be high to facilitate commercialization at scale.

The four seed varieties and the dried feed have distinguishing characteristics that might make farmers prefer one over another (see details in Ohmstedt & Mwendia, 2018). For example, the Cayman variety is tolerant to water logging unlike the other hybrids; the Cobra variety is relatively taller than the others and is best for cut-and-carry; the Mulato variety is resistant to spittlebug and has both high forage yield and nutritive quality (Maass et al., 2015). The Panicum variety on the other hand is like the improved Napier grass but is leafy and is tolerant to shade (Ohmstedt & Mwendia, 2018). Boma Rhodes hay is superior to rice straw in terms of crude protein content, organic matter digestibility, lignin level, and ash content—high levels of lignin and ash reduce digestibility (Gummert et al., 2019). Due to its low nutritive value, pretreatment of rice straw is necessary to enhance livestock productivity. Following these differences, we hypothesized that the WTP for the four seed varieties, and the two dried feeds will be different —the difference in WTP reflecting dairy farmers' valuation of the differentiating traits for each of the products.

We used the Becker-De-Groote Marschak (BDM) mechanism to elicit the WTP as we describe in detail in the subsequent sections. WTP is important in informing the pricing of the improved forages, enhancing understanding of the priority agronomic traits for the farmers, and providing evidence on whether farmers are willing to pay a premium for the priority traits. Such information is important when designing interventions aiming to enhance utilization, commercialization, and adoption of improved forages.

We report the following main findings. First, we find that WTP is below the market prices for all the forage products except for Panicum Mombasa when we consider farmers in cooperatives only. Second, we find that there are no price differentials across the Brachiaria varieties, meaning that when varieties are closely related, farmers might have difficulties differentiating them. This inability to distinguish varieties based on their "improvements" might explain the slow uptake of improved varieties by farmers (De Groote & Omondi, 2023), especially when the rate at which farmers learn about the varieties is lower than the rate at which the varieties are released. Third, we find that dairy farmers are willing to pay a premium for the Panicum Mombasa variety relative to the Brachiaria varieties—we speculate that this might be caused by the similarities with Napier grass, the most popular forage among livestock keepers in Kenya. Lastly, we find that the WTP for the Boma Rhodes hay was significantly higher than that of ordinary hay, which is plausible given the superior traits of the former. Jointly, these results underscore the need to rethink mechanisms aiming to enhance utilization and adoption of the improved forages. WTP lower than the prevailing market prices for both the seeds and hay require innovative strategies to commercialize the improved forages at scale. As we alluded earlier, for commercialization at scale to happen, suppliers should be incentivized by high premiums (holding other things constant) to supply either the seeds or hay. Farmers are likely to pay a premium for the improved varieties

when they know the benefits of the improved traits—we find that prior experience with the improved forages positively and significantly influenced the WTP.

Our findings contribute to the ongoing discussion on demand for (and adoption of) improved varieties in developing countries (De Groote & Omondi, 2023; Walker et al., 2015). The superior traits of the improved varieties should offset the high prices and increase demand for them. Unfortunately, adoption of the varieties for many crops including staple crops is low in the developing world (Acevedo et al., 2020; Walker et al., 2015). Though several factors explain the low adoption, still lacking in the literature is evidence on the demand for the improved traits and the trade-offs farmers make when selecting varieties. Some studies have assessed these trade-offs for other crops such as maize (Marenya et al., 2022), but evidence is particularly scanty for improved forages. To the best of our knowledge, no study has assessed the demand for various traits in improved forage varieties (and dried feed). Gonfa (2015), a study closely related to ours only assessed the demand for improved forage seeds using survey questions. We extend the evidence by using an incentive-compatible experiment to measure the demand for the seeds and dried feed. Evidence has shown that the use of experiments as the one we use accurately reveals WTP compared to approaches such as open-ended ranking (Waldman et al., 2014).

We proceed as follows. Section 2 describes the methods we used. In section 3, we present our findings. The last three sections provide discussions of the results, limitations of the study, and conclusions in that order.

3.2. Methodology

3.2.1. Sample size and sampling strategy

We used a mix of probabilistic (random sampling) and non-probabilistic sampling (purposive sampling) to recruit 356 farmers into the study. Our selection of sampling strategy is

motivated by the nature of our study—production of improved forages is relevant to farmers who keep livestock and produce crops at the same time. We therefore targeted livestock farmers in the mixed crop-livestock production system in Meru County. We purposively selected four sub-counties namely Imenti Central, Imenti south, Imenti north, and Buuri, which are also the main dairy production zones in the county. Farmers in these sub-counties are more commercially oriented and are well organized partly because of the strong presence of dairy farmer cooperatives in the sub-counties. Evidence has shown that farmers in cooperatives are more likely to have better access to information, and other amenities such as veterinary services compared to non-cooperative members (Abebaw & Haile, 2013; Jitmun et al., 2020), factors which are likely to influence WTP for the improved forage varieties and dried feed. For this reason, we split our population into two strata namely cooperative, and non-cooperative farmers. For the cooperative strata, we purposively selected two cooperatives from each sub-county to adequately capture different dynamics such as number of active farmers for maximum variation and representativeness (Cash et al., 2022). The selected cooperatives were Buuri, Katheri, Kithurine, Githongo, Chure Dairy, Nyaki, Kaarithi, and Kathirune. We then randomly selected 30 farmers from the big cooperatives and 25 farmers from the smaller cooperatives—the number of farmers in the cooperatives varied from as low as 300 to as high as 9000. The selected farmers were invited to a central place for the experiment. We ended up with 215 cooperative farmers because some of the selected farmers failed to show up for the experiment. We used systematic random sampling to select non-cooperative farmers in which case we skipped three households to the next study participant. A farmer was selected if she/he practiced mixed farming (kept livestock and produced crops at the same time). The selected farmers were also invited to a central place for the experiment. A total of 141 farmers not in a cooperative turned up for the experiment.

3.2.2. BDM and WTP elicitation

We used the BDM mechanism (Becker et al., 1964) to elicit WTP for the seeds and the dried feed. Though the BDM mechanism generates rich information on an individual's WTP and is known to be incentive-compatible (Berry et al., 2020; Burchardi et al., 2021; S. Cole et al., 2020), some factors such as the literacy of the subjects can reduce its applicability in the field, and the reliability of the elicited WTP. For example, the elicited WTP can suffer from some biases mainly hypothetical bias and social desirability bias (Berry et al., 2020; Norwood & Lusk, 2011). Hypothetical bias arises when subjects have no experience with the product resulting in a significant difference in the WTP from hypothetical and non-hypothetical contexts. To minimize hypothetical bias, we used actual products seeds in the environment of the farmers (Harrison & List, 2004). Because of the bulkiness of hay however, participants were directed to specific locations where they could get the hay from if they purchased it. Social desirability arises when participants bid in a manner they perceive to be desirable, to for instance the researcher. To reduce the effect of social desirability, we incorporated a cheap-talk script aiming to instill truth telling (List & Price, 2016). Another limitation of BDM is that participants may not understand the bidding process, the so-called game-form recognition failure (Cason & Plott, 2014). We address this by incorporating a practice round with regular soap costing a maximum of Ksh. 20 to ensure that participants understood the bidding process.

Farmers taking part in the experiment were informed about the study 2-3 days to the day of the experiment. Following this short notice, we could not overrule the possibility of liquidity constraints for some farmers when asked to make an unplanned purchase. To address this problem, participants received an endowment (a participation token) of Ksh. 400 (1 USD was equivalent to Ksh. 120 when we conducted the study), which they would also use to buy the seeds or the dried

feed. However, we anticipated such an endowment to also influence WTP through the "house money effect" (Thaler & Johnson, 1990). We sought to reduce the "house money effect" using the cheap talk (List & Price, 2016). We emphasized to the participants the importance (consequences) of revealing (not revealing) their true valuation of the seeds and dried feed.

Lastly, the order in which products are presented to the participants is likely to influence participants' responses through the "order effect". In our case, we did not anticipate any order effect for the seeds because the seeds are all improved, are "visually differentiable", and the names did not allude to any of them being superior to the other, unlike the case for the dried feed where the names "ordinary" hay and Boma Rhodes hay might alter farmers' perceptions and valuations of them. For example, participants may undervalue ordinary hay just because of the name, or because they think they were expected to undervalue the ordinary hay by the researcher, the so called "social desirability effect". We therefore control for the "order effect" for the dried feed by randomly varying the hay first presented to the farmer in addition to the cheap talk script. We also gave the research assistants instructions to stick to the information on the information sheets.

3.2.3. Description of the experiment and data collection

The experiment was conducted in the month of November 2022, which falls within the short rains season. However, because of depressed rains, the condition of natural pastures in Meru County at the time of the study was fair to poor (National Drought Management Authority; NDMA, 2022). The experiment was carried out by 10 trained research assistants, most of whom were able to speak the local language. The research assistants were recruited from a pool of research assistants who had worked with the research team before. The research assistants collected demographic data before the start of the experiment using an electronic semi-structured questionnaire. The aim of this arrangement was to ensure a good rapport between the research

assistants and the participants before conducting the experiment. The data collection and the experiment followed the regulations by the Institutional Review Board of the Alliance of Bioversity International and CIAT (approval number 2022-IRB60), which included obtaining full consent from the participants, signing a consent form before the start of the exercise, and observing Covid-19 protocols. Consent was verbally sought—the research assistants read aloud the objectives of the study, measures to ensure confidentiality of the collected data, and the rules of the experiment to the farmers. The farmers were also informed that they would withdraw from the study at any point if they got uncomfortable but still receive the full participation token.

We started the experiment by presenting information sheets on the attributes of the seeds and hay to the participants alongside the seeds, 50 grams of each variety—on average 3.2 Kgs of seed are required to plant 1 acre piece of land (Ohmsedt et al., 2018). The seeds were presented in brown bags that were well labelled. The information presented was obtained from Ohmstedt & Mwendia (2018), and from consultations with forage experts working in the county. In addition to text, the information sheets also contained images of the forages to enhance farmers' comprehension of some of the attributes. The information provided about the seeds included forage palatability, digestibility, crude protein content, tolerance to water logging, tolerance to drought, water requirement, planting density, planting depth, germination, days to first cut, time to rotation, plant height, production potential, soil fertility requirement, and adaptability to acidic soils (see Figure 3.1, more details in the appendix). The information provided about the hay included hay palatability, digestibility, crude protein content, dry matter, crude fiber, lignin, neutral detergent fiber (NDF), acidic detergent fiber (ADF), ash, organic matter digestibility, and nitrogen digestibility. All these properties were well explained to the farmer in the local language. The information was presented one variety at a time after which the research assistants then read all

the instructions on the bidding, emphasizing that though the participant bid for all the six products, one could only buy one product randomly drawn from a bag with six cards, each card representing each of the six products.

Brachiaria cv. Cayman

Characteristic	Rating
Palatability	High
Digestibility	High
Crude protein content	Up to 17% (depending on soil fertility)
Tolerance to water logging	High
Tolerance to drought	Good
Tolerance to shade	Poor
Water requirement	Min. 800 mm/year
Planting density	8 -10 kg/ha, zero tillage
Planting depth	1 - 2 cm
Germination	7 – 21 days
Days to first cut	90 – 100 days
Time in rotation	25 – 30 days (wet season); 60 – 70 days (dry season)
Plant height	80 – 110 cm
Production potential	Up to 15 tons fresh material/ha every 10 weeks in rainy season
Soil fertility requirements	Medium to high
Adaptability to acidic soils	High
Resistance to spittlebug	High

Other characteristics

1. Tillered growth
2. In moisture conditions, this variety develops early and has many decumbent stems
3. Can withstand poor drainage

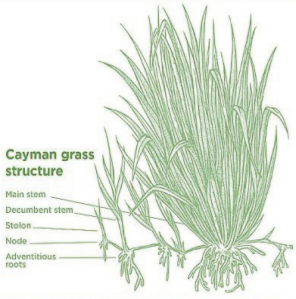




Figure 3.1: Sample of the information sheet

Before farmers bid for the products, we had a practice round with a 50 grams bar of soap to ensure that farmers understood the bidding process. We followed the conventional procedure for BDM (see for example Berry et al., 2020). The farmers were asked to state the maximum price they would pay for the soap. The participants were then asked whether they were willing to adjust their bids for the soap. The bids were then adjusted (or not) based on the participants' responses.

The participants were then asked to pick a piece of paper from a bag containing three pieces, each piece with a price on it namely Ksh. 5, Ksh. 10, Ksh. 15. A participant would purchase the soap if her bid was greater than the picked price—the buying price was the price picked from the bag.

Once the participants understood the bidding process, they were then asked to bid for each of the six products following the same procedure as in the practice round. This required the research assistant presenting the products again one at a time for the farmers to bid for each. The bidding was then followed by a random selection of a product to be purchased. Participants were offered a bag with six cards, each card representing each of the six products and asked to select a card. The participant was then offered another bag containing 4 prices and asked to pick a card. If the price on the card was lower than the price she bid for the product, she bought the product at the price on the card (Ksh. 150, Ksh. 200, Ksh. 250, Ksh. 300) otherwise, she did not buy the product. The cost of the product and the soap was then deducted from the Ksh. 400 participation token for the participants who purchased the forage product and the soap. The remaining amount was transferred to the participant via a mobile platform (Mpesa) at the end of the experiment. Participants who did not buy a product or the soap received the full amount of Ksh. 400.

3.2.4. Estimation approach

We use a mixed effects model to assess the WTP for both the seeds and the dried feed to take into account the variability of the WTP across the forage products as well as across the farmers simultaneously (Brown, 2021). In other words, the mixed effects model contains both random effects from participants, and fixed effects from the products, strata, and enumerators. The mixed effects model was executed in the R programming language as in Bates (2022). We estimate separate equations for the seeds and hay because these are two different products of the value chain

though the results from the separate estimations jointly help us to draw useful conclusions. The model for the seed estimation was specified as in equation (E.3.1):

$$Bid_{iks} = \alpha + \sum_{k=1}^{4} \beta_k Seed_{iks} + \omega_i X_{iks} + S_s + E_s + \varepsilon_{iks}, \quad \text{(E.3.1)}$$

where Bid_{iks} is the bid for participant i in strata s for seed variety k, $Seed_{iks}$ is a vector of the 4 seed varieties, X_{iks} are socio-economic factors, S_s are the sampling strata (cooperative and non-cooperative farmers), E_s are enumerator effects, while ε_{iks} is an error term. Our goal in equation 3.1 is to test the hypothesis $\beta_k = 0$, implying that the WTP for the seeds are not statistically different from a reference variety. For the hay, we estimate two sets of equations, equation 3.2 and equation 3.3. Equation (E.3.2) includes the hay dummy (Hay_{ihs}) only. ε_{ihs} is also an error term as in equation (E.3.1).

$$Bid_{ihs} = \alpha + \sum_{h=1}^{2} \beta_h Hay_{ihs} + \varepsilon_{ihs} \quad \text{(E.3.2)}$$

As in equation 3.1, the coefficients (β_h) represent the WTP for the two types of hay. In this case, we also test the hypothesis $\beta_h = 0$, implying that the WTP for the two types of hay are not statistically different. In equation (E.3.3), we include socio-economic factors X_{ihs}, sampling strata S_s, and enumerator effects (E_s) as in equation 3.1, and the order (O_{ihs}) dummy, which captures the order in which the information about the hay was presented. ε_{ihs} is an error term as before.

$$Bid_{ihs} = \alpha + \sum_{h=1}^{2} \beta_h Hay_{ihs} + \gamma_h O_{ihs} + \omega_i X_{ihs} + S_s + E_s + \varepsilon_{ihs} \quad \text{(E.3.3)}$$

Lastly, using the same framework, we assess the factors influencing the likelihood of farmers stating bids greater than the prevailing market prices. Our WTP in this case is a binary outcome, so we estimate a probit model as in equation (E.3.4):

$$WTP_{ijs} = \alpha_0 X_{ijs} + \gamma_h O_{is} + S_s + E_s + \varepsilon_{ijs}, \quad \text{(E.3.4)}$$

where WTP_{is} is an indicator equal to 1 if farmer *j* stated a bid greater than the prevailing market price for product *i,* and 0 otherwise. All the other arguments are as in the previous equations. In this estimation, our interest is to test the hypothesis $\alpha_0 = 0$, implying that the demographic factors do not influence the likelihood of stating bids greater than the prevailing market prices. Some studies such as Berry et al. (2020) have shown that individual characteristics do not explain the individual's WTP for a product.

3.3. Results

We provide summary statistics of the data in Table 3.1. Overall, most of the participants (57.1%) are women. Ninety eight percent of the farmers kept dairy cows, and 92% keep livestock for commercial purposes. Most farmers (74%) use zero grazing as their main production system. Literacy levels are relatively high, about 71% of the farmers have above primary school education. Lastly, 33% of the farmers earn a monthly income of more than 30,000 Kenyan shillings. The average age of the study participants is 48 years, while the average land holding is 1.95 acres. The number of years of experience in livestock production is on average 15 years.

Table 3.1: Summary statistics

Variable	Description	Overall (n = 356)		Non-cooperative (n = 141)		Cooperative (n = 215)		P-value (Cooperative vs non cooperative)
		Mean	SD	Mean	SD	Mean	SD	
Categorical variables								
Gender	1= Participant is male; 0 = Participant is female.	0.42		0.42		0.42		1.000
Main reason for keeping cattle	1 = Subsistence; 0 = Commercial.	0.08		0.14		0.05		0.010
Education	Respondent's highest level of education: 1 = Primary level education; 0 = Above primary level education.	0.39		0.42		0.37		0.444
Important livestock type	The main livestock type: 1 = Dairy; 0 = Beef.	0.98		0.94		0.99		0.007

Majority breed	1 = Pure exotic; 0 = Others.	0.83		0.77		0.87		0.011
Monthly income	Average monthly income:1 =More than Ksh. 30,000; 0 = Less than Ksh. 30,000.	0.33		0.24		0.38		0.008
Production system	Main production system:1 = Zero grazing; 0 = Others.	0.74		0.69		0.78		0.064
Received a loan after application	1 = Yes; 0 = No.	0.96		0.92		0.99		0.257
Prior experience with improved forages	1 = Participant has planted an improved forage before; 0 = Otherwise.	0.51		0.31		0.65		0.000
Who owns the cattle	1 = Respondent; 0 = Others.	0.47		0.46		0.48		0.822
Continuous variables								
Age (years)	Age of the respondent.	48.43	13.35	46.09	14.33	49.96	12.46	0.007
Land size	Land in acres owned by the respondent.	1.95	1.71	1.77	1.56	2.08	1.8	0.098
Household size	Number of people in the household.	4.45	1.63	4.6	1.86	4.35	1.46	0.171
Frequency of seeking for vet services	Average number of times the farmers seeks for vet service in a year.	4.27	4.51	12.93	12.73	16.47	12.53	0.010
Experience	Number of years the respondent has kept livestock.	15.07	12.71	1.8	2.28	2.09	1.67	0.171
Distance to nearest market	Distance to nearest market in Km.	1.97	1.97	1.77	2.56	2.14	1.78	0.106
Distance to nearest agrovet	Distance to nearest agrovet in Km.	2.00	2.13	4.42	4.66	4.17	4.41	0.608

Disaggregation by cooperative membership shows that farmers in the two strata differed in several respects. For example, 99% of the farmers in cooperatives keep dairy cows compared to 94% of those not in a cooperative, 87% of those in cooperatives keep pure exotic breeds compared to 77% of those that do not belong to a cooperative. Sixty-five percent of cooperative farmers had prior experience of improved forages compared to only 31% of the farmers not in cooperatives, a difference that is statistically significant. In addition, non-cooperative farmers were significantly

younger compared to those in a cooperative. Cooperative farmers also tended to seek veterinary services more frequently than their non-cooperative counterparts.

3.3.1. Willingness to pay for the products by cooperative membership

We summarize the WTP for the six products by cooperative membership (Table 3.2). Overall, the WTP for all the products except ordinary hay are statistically different for farmers in cooperatives and those that are not. While the WTP for all the six products was below the prevailing market prices for farmers not in cooperatives, their counterparts in cooperatives were willing to pay 16% more over the market price for the Panicum Mombasa variety. The difference between the WTP and the prevailing market was marginal (1% less than the market price) for Mulato for the farmers in cooperatives. The biggest margin between the average WTP and the prevailing market prices were registered for the Cayman variety (25% and 44% of the prevailing prices for the farmers in cooperatives and those that are not respectively).

Table 3.2: Summary of WTP by cooperative membership

		Farmers in cooperatives (n = 215)			Farmers not in a cooperative (n = 141)			
	Prevailing market price (Ksh)	Mean WTP for Cooperative members (Ksh)	SD (Ksh)	WTP – Prevailing price (% of prevailing market price)	Mean WTP for farmers not in cooperative (Ksh)	SD (Ksh)	WTP – Prevailing price (% of actual price)	P-Value WTP cooperative vs non cooperative
Seed products								
Panicum Mombasa	200	232	195.24	16	162	126.17	-19	0.000
Cayman	275	207	164.78	-25	153	106.90	-44	0.001
Cobra	225	207	170.00	-8	154	106.18	-32	0.001
Mulato	200	198	152.31	-1	159	114.75	-21	0.011
Dried feed								

Boma Rhodes hay	300	247	107.88	-18	219	124.12	-27	0.024
Ordinary hay	250	196	104.95	-22	193	108.89	-23	0.782

Note: SD is standard deviation.

Next, we assess whether there are differences in the distributions of the bids for the various products for farmers in cooperatives and those that are not. Though participants bid more for the Panicum Mombasa variety (Figure 3.2, panel A and B), the kernel density for the Panicum Mombasa does not stochastically dominate those of the Brachiaria varieties. Similarly, the density distribution of the Boma Rhodes hay does not stochastically dominate that of the ordinary hay (Figure 3.2, panel C and D).

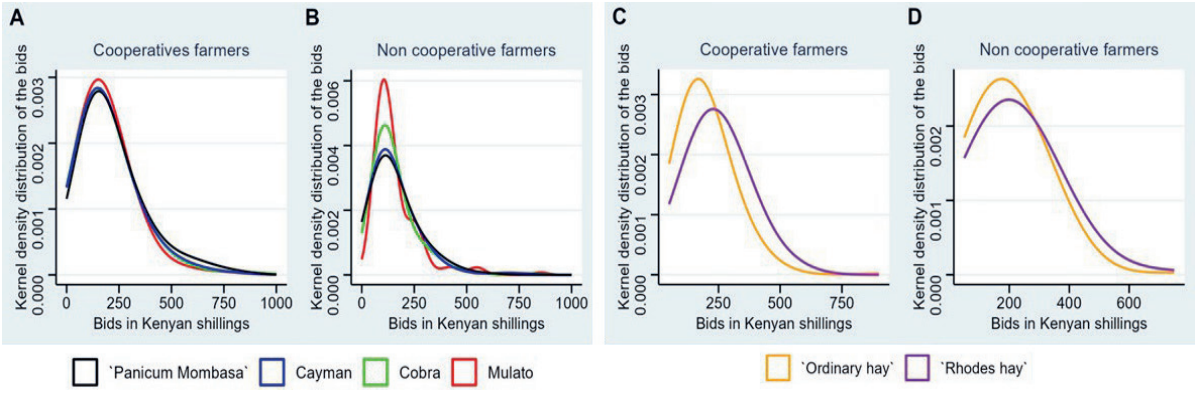


Figure 3.2: WTP kernel density distributions

3.3.2. Regression analysis of the WTP

The results from the regression analysis are presented in Table 3.3. Models 1 and 2 are mixed effects regression results for the seeds while models 3 and 4 are results for hay. The reference (constant) in the seeds regressions is the Mulato variety. The significant constant shows that the WTP is statistically different from zero. Models 1 and 2 show no significant difference in the WTP across the Brachiaria varieties. However, the results show a significant difference in the WTP for the Panicum Mombasa variety relative to the Mulato variety, which implies that farmers

are willing to pay Ksh. 22 more on average for the Panicum Mombasa variety compared to the Mulato variety. The reference (constant) in models 3 and 4 is the ordinary hay. The results show that the WTP for the Boma Rhodes hay is statistically different from that of the ordinary hay—farmers are willing to pay Ksh. 41 more on average for the Boma Rhodes relative to the ordinary hay.

Table 3.3: Regression analysis of WTP

	Model 1	Model 2	Model 3	Model 4
Constant	177.284***	183.766***	194.108***	210.544***
	(27.047)	(44.894)	(7.995)	(29.903)
Cayman	3.511	3.511		
	(4.063)	(4.063)		
Cobra	3.419	3.419		
	(4.063)	(4.063)		
Panicum Mombasa	22.278***	22.278***		
	(4.063)	(4.063)		
Boma Rhodes hay			40.772***	40.772***
			(3.758)	(3.758)
Other controls	No	Yes	No	Yes
Strata dummies	Yes	Yes	Yes	Yes
Enumerator dummies	Yes	Yes	Yes	Yes
Order dummies	No	No	No	Yes
Number of farmers	356	356	356	356
Number of observations	1424	1424	712	712

Note: Significance: *** = $p < 0.01$; ** = $p < 0.05$; * = $p < 0.1$. Control variables included in the regression are age, education, household size, main reason for keeping livestock, land size, prior experience with improved forages, main production system, monthly income, frequency of seeking for veterinary services, and distance to nearest market.

We also estimate separate regressions for seeds and hay to determine the demographic factors that influenced the likelihood of farmers bidding over the market prices (Table 3.4). The results in the overall column include both seeds and dried feed, while the seeds and dried feed columns show results for seeds and dried feed respectively. Across the three models, age had a strong consistent negative influence on the likelihood of bidding more than the market prices, implying that demand for both the seeds and dried feed declines with age. Land size on the other hand had a significant positive influence on the likelihood of farmers bidding above the market prices for seeds at 10% significance level—farmers with bigger land sizes were more likely to state bids greater than the prevailing market prices. This is plausible because most of the farmers mentioned that scarcity of land is one of the main hindrances to cultivation of the improved forage varieties (see appendix). Farmers who had prior experience with improved forage varieties tended to bid more, implying that knowledge about the varieties is important in driving demand up—this association is significant at 1%. Practicing zero grazing as the main production system also strongly and positively influenced the likelihood of farmers stating bids greater than the market prices for both seeds and dried feed. Farmers with monthly incomes above 30,000 tended to bid less for hay—this association is significant at 5% significance level, while those who owned the livestock tended to bid more for the seeds.

Table 3.4: Factors affecting WTP

	Overall	Seeds	Dried feed
(Intercept)	−2.000*	−3.730**	−2.289
	(0.841)	(1.234)	(1.415)
Age	−0.050***	−0.066***	−0.067***
	(0.013)	(0.019)	(0.023)
Education (Above-primary level education)	0.109	0.176	0.320

	(0.350)	(0.503)	(0.574)
Household size	0.122	0.205	0.264
	(0.102)	(0.142)	(0.167)
Main reason for keeping livestock (Subsistence)	−0.382	−0.196	−1.006
	(0.604)	(0.872)	(0.909)
Land size	0.090	0.235*	0.169
	(0.103)	(0.142)	(0.172)
Prior experience with improved forage (Yes)	1.216***	1.733***	1.188**
	(0.343)	(0.477)	(0.562)
Main production system (Zero grazing)	1.553***	2.111***	1.657***
	(0.407)	(0.603)	(0.642)
Monthly income (More than 30,000)	−0.471	−0.260	−1.610**
	(0.369)	(0.510)	(0.635)
Frequency of seeking for veterinary services	0.033	0.054	0.017
	(0.037)	(0.051)	(0.061)
Distance to nearest market	−0.040	−0.102	0.020
	(0.088)	(0.130)	(0.140)
Who owns the livestock (Respondent)	0.517	0.940**	0.316
	(0.334)	(0.471)	(0.535)
Enumerator controls	Yes	Yes	Yes
Strata controls	Yes	Yes	Yes
Number of farmers	356	356	356
Number of observations	2136	1424	712

Significance: *** = $p < 0.01$; ** = $p < 0.05$; * = $p < 0.1$

3.4. Discussions

In this study, we sought to assess the WTP for improved forage seeds and dried feed varieties of farmers in cooperatives and those that are not. We find that farmers in cooperatives revealed a higher WTP for the products compared to those who did not belong to a cooperative, an effect we speculate is driven by better access to information and services as it has been shown in some studies (for example Abebaw & Haile, 2013; Jitmun et al., 2020). The low WTP (below prevailing market prices) for the improved varieties with the exception of Panicum Mombasa is a common trend also in other crops (Mastenbroek et al., 2021; Walker et al., 2015). This trend has implications on the commercialization of the improved forages value chain. As we noted earlier, farmers' willingness to pay a premium for either the seeds or the dried feed or both can incentivize more suppliers to supply the seeds or dried feed ultimately promoting commercialization. However, our results do not depict farmers as willing to pay premiums especially for the Brachiaria varieties, which corroborate evidence in the literature (Morrison et al., 2023). This calls for innovations that can lower the costs of producing, breeding, and transporting the seeds so that market prices match farmers' WTP.

The wide margins between farmers' WTP and the prevailing market prices for the Cayman variety are plausible because the study areas are not prone to waterlogging. However, not observing a significant difference in the WTP across the Brachiaria varieties despite the differences across them such as tolerance to waterlogging (for the Cayman), tolerance to spittlebug (the Mulato variety), or suitability for cut-and-carry (Cobra) is a surprising result. Three main issues arise from this finding. First, either agronomic traits are not important criteria for improved forage variety selection by farmers as some studies have pointed (for example Macours, 2019), second, dairy farmers do not know (did not get) the differences across the Brachiaria varieties, or third, BDM as

a mechanism is limited in capturing individuals' valuations of some product attributes, especially when the difference in attributes is "subtle" (see for example Ariely et al., 2003). . The first two issues are an impetus to train farmers and stockists alike—evidence has shown that stockists are an important channel through which farmers obtain information about new varieties (Dar et al., 2020)—on the benefits of the improved traits, and creating opportunities where farmers experiment with the forages. The importance of farmer training is evident from our results; farmers who had experience with the improved forages before tended to bid more. Studies such as Channa et al. (2019) also show that prior awareness about a new technology influenced farmers' WTP for the technology. Simtowe et al. (2019) found that exposure to drought tolerant seeds increased their adoption by about 8%. More research is needed on the third issue on BDM's ability to sufficiently capture individual's valuations of "subtle" but important differences across products because on one hand, the WTP for the Brachiaria varieties is not statistically different though the varieties have important distinguishing attributes, while on the other hand, the WTP for the Boma Rhodes a "superior" product is statistically different from that of the ordinary hay an "inferior" product, a clear indication of greater valuation of the superior traits by farmers. It is not clear from the literature the circumstances under which WTP captures the valuation of the "subtle" differences across products.

The significant associations between demand for the forage products (bidding more than the prevailing market price) and some socio-demographic factors namely age of the farmer, whether farmers practiced zero grazing as the main production system, land size owned by the farmer, monthly income, and whether the animals are owned by the farmer are plausible (Beshir, 2014). The negative influence of age on WTP might arise because of declining interest in new technologies by older farmers, and slowness in understanding the attributes of the new

technologies (Fadeyi et al., 2022). The positive association between the WTP and land size underpins limited options to increase crop diversity for farmers with small farm sizes. Previous evidence has highlighted competing uses for land in Kenya as a major hindrance to farmers adopting cultivated forages (Maina et al., 2022). This implies that promotional efforts to cultivate improved forages should target farmers with relatively bigger farm sizes, with mechanisms in place to ensure that farmers with smaller farms have access to the forages. Cooperatives can also be used as an avenue for the promotion of the improved forages. The strong association between the WTP and whether a farmer practiced zero grazing arises from the likely dependence on cultivated forages by these farmers who mostly do cut-and-carry.

Our findings have several policy implications on the efforts aiming to promote the adoption, utilization, and commercialization of improved forages. The low WTP for both seeds and hay require innovations that reduce the costs of production, certification, and transportation of the seeds without disrupting the forages value chain. One such innovation is the promotion of farmer-led seed production through contracts, a model that is both profitable and enhances involvement of the private sector (Mishra et al., 2016). Engaging farmers in producing the improved forage seeds is also likely to address other challenges such as access to the seeds (Maina et al., 2022)—because small scale farmers depend on informal markets for inputs (Michelson et al., 2023)—while at the same time foster peer-learning, which is an important channel through which small scale farmers learn about new technologies (Benyishay & Mobarak, 2019; Conley & Udry, 2010; Shikuku et al., 2019). Such an arrangement requires enabling legislature, for example in certification and quality assurance of the seeds. Lastly, the influence of some demographic factors on WTP implies that promotional activities could be targeted to certain types of farmers such as young farmers, farmers with larger land sizes, those using zero grazing, and those in

cooperatives as we highlighted earlier. However, such an approach is likely to further marginalize farmers in the extensive production systems from the forages value chain, yet they are usually the most affected by feed scarcity, and low productivity. Therefore, the targeting should be accompanied by efficient coordination mechanisms across value chain actors to ensure that farmers who cannot produce the forages (because of limited access to land suitable for forage production for instance) are linked with farmers who produce the forages or with traders who are able to source the forages from the farmers who produce. Such a linkage is likely to create demand for dried feed, which will in turn incentivize farmers to cultivate the improved forages. Increased cultivation of the forages will translate to high demand for the improved seeds, and high productivity of the forages, high productivity of livestock, and ultimately increase farm incomes, availability of food, and reduce the adverse impacts of the livestock sector to the environment.

3.5. Limitations of the study

Though the descriptive summaries of some characteristics of our sample such as the proportion of women farmers, the average household size, and the average age of the farmers are comparable to those in other studies such as Muriithi et al. (2022) and Birch (2018), our sample comprises of farmers that are relatively commercial, better educated and have better access to information and services compared to an average farmer in Meru County and Kenya in general. This limits the generalizability of our results. Therefore, more assessments comparing the WTP of farmers in different farmer segments (for example based on geography, commercialization level, and production systems) should be done for completeness. In addition, aspects such as seasonality of the forages, which we do not consider in this study should be considered in the assessments. Another limitation of our study is that like many studies, we use the standard BDM procedure without controlling for other pitfalls of the BDM mechanism such as “anchoring” (Ariely, 2008),

"house money effect", even though we used a cheap talk to instill truth telling, and the "order effect" on the WTP for the seeds—we only conclude that there was no "order effect" because we do not see an effect on the WTP for the dried feed. Future studies assessing the WTP for the improved forages should endeavor to control for these effects.

3.6. Conclusion

Though improved forages have the potential of increasing productivity and addressing the rampart problem of livestock feed shortages in developing countries, poor access by dairy farmers and the high prices of the improved forage seeds hinder utilization and adoption. In this study, we have assessed dairy farmers' WTP for four varieties of improved forages namely *Brachiaria Cayman*, *Brachiaria Mulato*, *Brachiaria Cobra*, and *Panicum Mombasa*, and two types of dried feed namely rice straws and Boma Rhodes hay using an incentive-compatible experiment. Our key finding is that the superior traits of the improved forage seeds do not offset the high prices. We found big margins between the WTP for the products and the prevailing market prices despite the prevailing dry spell that would have made feed shortage more salient. We conclude that such big margins can be offset by reducing the costs associated with the production, certification, storage, and transportation of the seeds. In addition, unlike other crops such as maize and beans, the forages can be propagated through vegetative planting material, an impetus for future studies to assess the demand for vegetative material relative to seeds.

Our study also links variety specific traits to the WTP for the varieties. Our key finding in this regard is that the WTP does not reflect preference for specific traits, contrary to our expectation especially for the Brachiaria varieties which are closely related. This result implies that more awareness creation and sensitization about the benefits of the various improved traits should be encouraged to ease comprehension and decision making by farmers when selecting varieties.

Furthermore, dairy farmers should be given opportunities to experiment with the various varieties—we found that participants with prior experience with the seeds bid more for the forage products on average. Comparison of WTP for Brachiaria varieties and Panicum Mombasa showed that overall, dairy farmers are willing to pay a premium albeit small (Ksh. 5) over the prevailing market price, while farmers in cooperatives (a sub-group in our sample) are willing to pay a higher premium (Ksh. 32) for the Panicum variety. We have only speculated that similarities between the Panicum Mombasa variety and improved Napier grass might be driving the high WTP. More research is needed to understand why farmers are willing to pay a premium for the Panicum Mombasa relative to the Brachiaria varieties.

Lastly, though we have data on WTP for both the seeds and dried feed, we are not able to make a direct comparison between the WTP for seeds verses dried feed first because we there were no dried feed from the four varieties we assessed in the market at the time of the study, and second because these are two different types of products of the value chain, with different production dynamics. Future studies should find innovative ways of comparing the WTP for seeds and hay to shed more light on the economic feasibility of cultivated forages as a business.

Appendix 3

Appendix 3A: Main reasons for preferring either hay or seeds

Appendix Table 3.1: Main reason for preference for either hay or seeds

	Seeds	Hay
	n = 323	n = 33
Better quality	42 (13.0)	4 (12.1)
Easily available	48 (14.9)	11 (33.3)
It is cheaper	39 (12.1)	0 (0.0)
More economical and permanent solution	187 (57.9)	2 (6.1)
Palatability	5 (1.5)	5 (15.2)
Ready to use	0 (0.0)	3 (9.1)
Scarce land	2 (0.6)	8 (24.2)

Note: Percentages in parenthesis.

Appendix 3.B: Information sheets

Appendix 3.B.1: Panicum maximum cv. Mombasa (Mombasa grass)

Characteristic	Rating
Palatability	Good
Digestibility	?
Crude protein content	8 - 14% (depending on soil fertility)
Tolerance to water logging	Low
Tolerance to drought	Good (Tropical seeds, low (SOEST)
Tolerance to shade	Poor
Water requirement	Min. 800 mm/year
Planting density	4 -5 kg/ha
Planting depth	1 - 2 cm
Germination	10 – 28 days
Days to first cut	75 – 100 days
Time in rotation	40 – 45 days
Plant height	2 meters
Production potential	20 – 40 tons dry matter/ha/year
Soil fertility requirements	High
Adaptability to acidic soils	?

Other characteristics

1. Stems do not have hair or wax
2. Suitable for grazing, silage, and fresh in feeding trough
3. Not suitable for hay due to difficult drying characteristics
4. Forage quality is excellent





Appendix 3.B.2: Brachiaria cv. Cayman

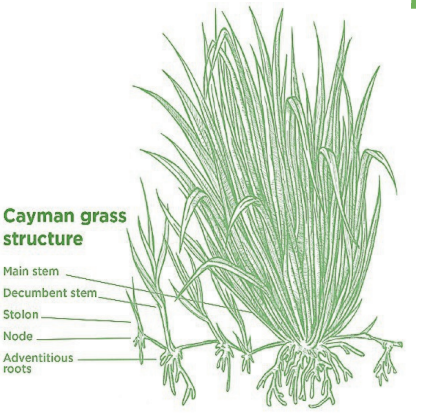
Characteristic	Rating
Palatability	High
Digestibility	High
Crude protein content	Up to 17% (depending on soil fertility)
Tolerance to water logging	High
Tolerance to drought	Good
Tolerance to shade	Poor
Water requirement	Min. 800 mm/year
Planting density	8 -10 kg/ha, zero tillage
Planting depth	1 - 2 cm
Germination	7 – 21 days
Days to first cut	90 – 100 days
Time in rotation	25 – 30 days (wet season); 60 – 70 days (dry season)
Plant height	80 – 110 cm
Production potential	Up to 15 tons fresh material/ha every 10 weeks in rainy season
Soil fertility requirements	Medium to high
Adaptability to acidic soils	High
Resistance to spittlebug	High

Other characteristics

1. Tillered growth

2. In moisture conditions, this variety develops early and has many decumbent stems

3. Can withstand poor drainage







Appendix 3.B.3: Brachiaria cv. Cobra

Characteristic	Rating
Palatability	High
Digestibility	High (69%)
Crude protein content	Up to 17% (depending on soil fertility)
Tolerance to water logging	Low
Tolerance to drought	Good
Tolerance to shade	Poor
Water requirement	Min. 800 mm/year
Planting density	8 -10 kg/ha, zero tillage
Planting depth	2 cm
Germination	7 – 21 days
Days to first cut	90 days
Time in rotation	30 – 45 days (wet season); 75 days (dry season)
Plant height	?
Production potential	More than 20 tons dry matter/ha/year
Soil fertility requirements	Medium to high
Adaptability to acidic soils	High
Resistance to spittlebug	High

Other characteristics

1. Has erect growth with well-defined tussocks making it ideal for cut and carry

2. Recovers quickly from cutting and grazing









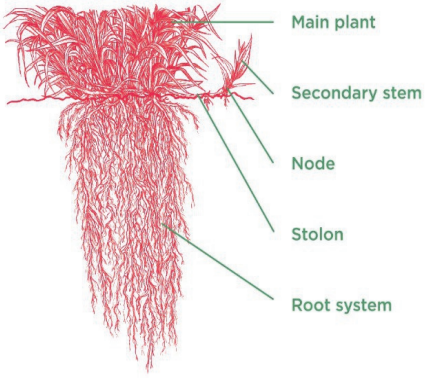
Appendix 3.B.4: Brachiaria cv. Mulato II

Characteristic	Rating
Palatability	High
Digestibility	High
Crude protein content	Up to 18% (depending on soil fertility)
Tolerance to water logging	Poor
Tolerance to drought	Good
Tolerance to shade	Poor
Water requirement	Min. 800 mm/year
Planting density	8 -10 kg/ha, zero tillage
Planting depth	2 cm
Germination	7 – 21 days
Days to first cut	70 - 80 days
Time in rotation	25 – 45 days (wet season); 60 - 70 days (dry season)
Plant height	80 – 100 cm
Production potential	On less fertile land (ph 4.7) 14 – 17 tons dry matter/ha/year. On highly fertile soils (ph. 6.3) up to 35 tons dry matter/ha/year
Soil fertility requirements	Medium to high
Adaptability to acidic soils	High
Resistance to spittlebug	High

Other characteristics

1. Recommended for regions acid soils of medium to low fertility

2. It can withstand prolonged periods of drought and high temperatures







Appendix 3.B.5: Boma Rhodes attributes

Characteristic	Rating
Palatability	High but declines as the plant grows older especially during seeding
Crude protein content	8 – 50% when flowering but declines as the plant grows older
Dry matter	86%
Crude fibre	35%
Lignin	5.6%
Neutral detergent fibre (NDF)	75%
Acid detergent fibre	41%
Ash	10%
Organic matter digestibility	63%
Energy digestibility	59%
Nitrogen digestibility	9%

Appendix 3.B.6: Ordinary (rice straws) hay

Characteristic	Rating
Palatability	High but declines as the plant grows older especially during seeding
Crude protein content	3 – 6%
Dry matter	92 – 96%
Crude fibre	35%
Lignin	5.6%
Neutral detergent fibre (NDF)	69%
Acid detergent fibre (ADF)	42%
Ash	18%
Organic matter digestibility	50%
Energy digestibility	47%
Nitrogen digestibility	2%

Chapter 4

When willingness to pay is not enough: Preference reversals between actuarially identical index insurance products

Jamleck Osiemo, Francesco Cecchi, Cyrus Muriithi, Caroline Mwongera

Abstract

This paper examines whether willingness to pay (WTP) is sufficient to recover farmers' preferences for agricultural risk management products. Using a framed field experiment with index insurance, we compare a single-peril (SP) and a multiple-peril (MP) product that are actuarially identical in expected payouts and premiums but differ in exposure to catastrophic losses. We find that average WTP is statistically indistinguishable across the two products. However, when given the opportunity to switch, farmers display a pronounced preference for the MP product. The observed preference reversal is unlikely to be driven by elicitation noise. WTP responds systematically to product quality and is robust across elicitation mechanisms. Instead, the evidence is consistent with preferences shaped by heterogeneous subjective risk perceptions and precautionary behavior such as sensitivity to tail risk, dimensions not fully captured by price alone. These findings suggest that insurance products tailored to farmers' heterogeneous risk perceptions and profiles, particularly those offering protection against rare but severe losses, may achieve higher uptake. The results also indicate that WTP alone may be insufficient to fully characterize farmers' preferences for risk management innovations.

Key words: Willingness to pay; Insurance; Innovation; Agriculture; Preferences; Kenya

4.1. Introduction

Agricultural innovations are widely viewed as central to addressing persistent challenges in small-scale agriculture, including low productivity, food insecurity, poor nutrition, and exposure to risk (Gaffney et al., 2019; Suri & Udry, 2022). Farmers' ex-ante valuation of these innovations particularly their attributes plays a critical role in adoption decisions (Macours, 2019). Understanding how farmers value (new) technologies is therefore essential for the design of the technologies, policy targeting, and scale-up.

Willingness to pay (WTP) is widely used to elicit valuations and infer demand, under the assumption that preferences are well defined, internally consistent, and revealed by stated prices (Ariely et al., 2003; Canavari et al., 2019). However, a large body of evidence from behavioral and consumer research shows that preferences are often constructed and context dependent (Hoeffler & Ariely, 1999). Individuals frequently exhibit preference reversals: they choose one option while assigning a higher monetary valuation to another (O'Donnell & Evers, 2019). Such behavior violates the predictions of expected utility theory and raises concerns about the extent to which WTP captures underlying preferences.

This paper studies whether WTP alone is sufficient to infer farmers' preferences over insurance products that differ primarily in their exposure to tail risk. We focus on index-based crop insurance because demand has remained persistently low despite substantial policy interest (S. A. Cole & Xiong, 2017; Kramer et al., 2022; Platteau et al., 2017), underscoring the need for innovative products. Demand for index insurance is highly sensitive to product attributes, including the number of perils covered and the severity of losses insured (Ghosh et al., 2021; Veettil et al., 2024). While small-scale farmers are exposed to multiple, correlated risks (Komarek et al., 2020), most available products insure only a single peril. Multiple-peril index insurance is

potentially more attractive but is often prohibitively expensive or infeasible due to pricing and modeling constraints (Barnett, 2014).

We design and experimentally assess how small-scale farmers value an innovative multiple-peril (MP) index insurance product that is actuarially equivalent to a conventional single-peril product (SP) with equal expected payouts and premiums but differs in its tail-risk properties. The experimental design proceeds in two steps. First, we elicit farmers' WTP for either the SP or MP product. Second, we ask farmers whether they would like to switch between the two products. This design allows us to directly test whether valuation and choice are aligned for the two products.

To assess the reliability of WTP elicitation and rule out measurement error as the primary driver of the preferences, the experiment incorporates some validation checks. We compare WTP elicited using a Becker–DeGroot–Marschak (BDM) mechanism with WTP elicited through a take-it-or-leave-it (TIOLI) offer, allowing us to test sensitivity to the elicitation mechanism. We also examine whether WTP responds to variation in insurance quality, focusing on basis risk (non-performance), a key determinant of demand for index insurance (see for example Hill et al., 2016; Lichtenberg & Martinez, 2022).

Farmers were randomly assigned to either the SP or MP product, to one of two elicitation mechanisms (BDM or TIOLI), and to one of three basis risk levels (5%, 10%, or 15%). Valuations were elicited within an incentivized, risk-insurance game with real monetary payoffs. Collectively, these design features enable us to attribute observed differences in preferences to characteristics of the products—whether objective or subjectively perceived—rather than to artifacts of measurement error or elicitation noise.

We obtained three main findings. First, in the valuation stage, farmers state identical WTP for the SP and MP insurance products on average, consistent with the fact that the products are actuarially identical in premiums and expected payouts. Second, in the subsequent choice stage, preferences diverge sharply: 61 percent of farmers initially assigned to the SP product choose to switch to the MP product, whereas only 37 percent of those assigned to the MP product switch to the SP product. Thus, farmers' preference for MP insurance becomes apparent only when they are exposed to an alternative product. Third, validation exercises show that WTP responds to insurance quality (non-performance or basis risk) consistent with empirical evidence that basis risk reduces demand for index insurance (Clarke, 2016; Hill et al., 2016; Lichtenberg & Martinez, 2022). Lastly, consistent with Cole et al. (2020), we find no statistically significant differences in WTP across elicitation mechanisms (BDM versus TIOLI).

The observed preference reversal does not appear to reflect noisy or irrational decision-making; rather, it highlights a limitation of WTP to capture underlying preferences for risk-mitigation mechanisms (and perhaps other agricultural innovations). These preferences become more explicit when farmers are presented with an alternative product. Multiple factors may independently or jointly drive the observed switching behavior, and this study does not attempt to isolate these mechanisms. Nonetheless, subjective risk perceptions appear to play an important role. Farmers who switched from SP to MP frequently reported that both risks were important, and coverage against both was more attractive. Conversely, farmers who switched toward the SP product emphasized that drought is more severe and less controllable than pests, making full coverage against drought losses particularly attractive. Although these reported reasons could be interpreted as post-switching rationalization, evidence from machine learning analyses of switching behavior indicates that pre-intervention risk perceptions and prior shock experiences are

strong predictors of switching. This pattern is consistent with the view that underlying beliefs about the nature of risk and experience with risk induced shocks, rather than purely ex post justification, contribute to the observed preference shifts.

Preference for the MP product is consistent with aversion to tail risk, as farmers may be particularly sensitive to catastrophic outcomes (Di Falco & Chavas, 2009). Under a constant relative risk aversion (CRRA) utility framework, a second-order Taylor expansion of expected utility implies that higher variance and negative skewness reduce welfare. Because the SP and MP products are identical in expected payouts, differences in higher moments of the payout distribution may contribute to the relative attractiveness of the MP contract. This interpretation is consistent with the finding that precautionary behavior—specifically, prudence—emerges as a strong predictor of switching from SP to MP, suggesting a role for higher-order risk preferences in shaping product choice.

Having ruled out elicitation noise, these findings suggest that WTP alone may obscure economically meaningful heterogeneity in preferences, particularly when insurance products differ in their exposure to tail risk and when subjective risk perceptions vary across farmers. At the same time, the precise mechanisms underlying these patterns remain to be identified and warrant further investigation.

This paper contributes to two related strands of literature. First, it contributes to the literature on demand for index insurance by demonstrating that heterogeneity in farmers' risk perceptions (behavioral responses to tail risk) can generate preference reversals, even when insurance products are actuarially identical. While farmers could be exposed to the same risks (hazards), some farmers will place disproportionate weight on protection against rare but catastrophic losses, rendering a multiple-peril product that covers catastrophic losses across risks

more attractive. Others, however, appear to differentiate risks based on their perceived controllability, favoring a single-peril product that fully covers losses from a risk viewed as severe and beyond their control. From a policy and product design perspective, these findings underscore the importance of incorporating heterogeneity in farmer risk profiles when designing and promoting index insurance products (see for example Ceballos & Robles, 2020).

Second, this paper contributes to the contingent valuation literature by showing that WTP can exhibit internal coherence such as downward-sloping demand and sensitivity to product quality (Ariely et al., 2003; Tversky & Thaler, 1990), while failing to recover underlying preferences over products. We show that this limitation can be mitigated by complementing standard WTP elicitation with explicit choice-based validation. Eliciting WTP alongside a subsequent switching or choice task that makes key trade-offs salient allows preference reversals to be interpreted as reflecting underlying relevant considerations rather than valuation noise or choice inconsistency. This two-step approach preserves the informational advantages of WTP while anchoring valuations in revealed choices, thereby improving the ability of contingent valuation methods to capture preferences over attributes that are weakly reflected in prices.

The paper proceeds as follows. In the next section we describe the study design, elicitation of WTP, and data. In section 4.3, we discuss our empirical strategy. In section 4.4, we present the results. We then discuss the results and make conclusions in section 4.5.

4.2. Study design, elicitation of WTP, and data

4.2.1. Randomization

This study focuses on 700 farmers from Meru County in Kenya randomly assigned to a game-based intervention aiming to increase farmers' understanding of index insurance. The farmers were randomly assigned into either an SP (n_1 = 350) or MP (n_2 = 350) product (Figure 4.1). The SP product covered all losses from drought only, while the MP product covered major losses only from both drought and pests. Farmers in each of the two arms were again randomly assigned into either the BDM (n_3 = 175) or TIOLI (n_4 = 175) arms.

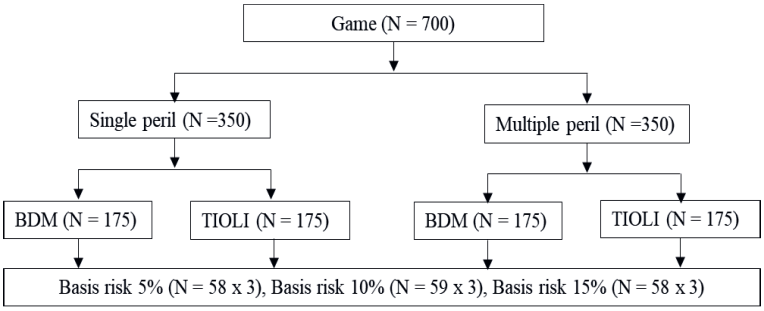


Figure 4.1: Randomization

For each of the BDM and TIOLI arms, farmers were further randomly assigned into either a 5% (n_5 = 58), 10% (n_6 = 59), or 15% (n_7 = 58) chance of product non-performance. The three levels of non-performance imply that farmers in the 5% level had a 5% chance of not receiving a payout after suffering a loss, those in the 10% level had a 10% chance of not receiving a payout while those in the 15% level had a chance of 15% of not receiving a payout. These levels of non-performance are considered realistic in developing countries (Lichtenberg & Martinez, 2022).

4.2.2. The game

The primary objective of the experimental game was to enhance farmers' understanding of crop insurance through experiential learning (Osiemo et al., 2025). The game comprised four core elements: (i) a hypothetical one-acre plot with an average yield of 12 bags of maize; (ii) an endowment of 2,000 units of game currency for insurance purchases; (iii) output market in which maize sold at 2,000 game currency per bag; and (iv) exposure to two production risks—drought and pests and diseases. Realized yields depended on stochastic risk outcomes conditional on players' decisions. In each round, yields deviated from the mean by ±4, ±2, or ±1 bag per risk, generating a maximum yield of 20 bags in favorable states and a minimum of 4 bags in adverse states. For example, simultaneous major losses from both risks resulted in a yield of 4 bags (12 − 4 − 4), while favorable realizations for both risks yielded 20 bags (12 + 4 + 4). The yield distributions were designed to approximate a symmetric distribution with high probability mass on moderate outcomes and low probability mass on extremes, while ensuring that the expected payouts—and hence premiums—of the insurance products were equal.

The experiment consisted of four independent rounds. The first round served as a practice session to familiarize participants with the game mechanics. The second round involved no insurance. In the third round, participants were offered crop insurance without non-performance risk, while in the fourth round, insurance was offered with a positive probability of non-performance (Appendices 4.B.2 and 4.B.4). In each insured round, all participants were eligible to purchase insurance, with purchase determined by whether the individual's stated WTP exceeded the randomly drawn strike price, as described in the next section.

4.2.3. Elicitation of WTP

4.2.3.1. BDM arm

We followed the standard BDM procedure (see for example Berry et al., 2020). Enumerators first explained the insurance products and their payout structures. Farmers were then asked to state the maximum price they were willing to pay for the product. Purchase decisions were determined by a randomly drawn offer price: each farmer selected one slip from a jar containing three possible prices (KSh 100, 300, and 500). These prices were chosen to bracket the actuarially fair premium (KSh 364). A farmer purchased insurance if her stated WTP exceeded the randomly drawn price, in which case the transaction price equaled the draw. The premium was deducted from the farmer's endowment of KSh 2,000.

While the BDM mechanism yields richer information on individual demand, it requires greater cognitive effort than simpler elicitation methods such TIOLI offers (Penn & Hu, 2018). To mitigate these concerns, the BDM procedure was implemented repeatedly across four game rounds, reducing the likelihood of game-form recognition failure. In addition, farmers gained experience with product outcomes through the risk game prior to valuation. Experimental evidence suggests that games enhance attention, feedback, and learning (Boyle et al., 2011), thus are likely to reduce hypothetical bias. Related approaches, such as virtual reality–based elicitation, provide supporting evidence for this mechanism (Fang et al., 2021).

4.2.3.2. TIOLI arm

As in the BDM arm, value in the TIOLI arm was elicited within the game context. The procedure for the TIOLI participants was as follows. We offered the farmer a jar containing the same three offer prices as those for the BDM group (100, 300, and 500 shillings). We asked the farmer to randomly select a price from the three. Next, we asked the farmer whether she would

buy the insurance at the selected price. If the answer was yes, the farmer then would hand the enumerator the amount equal to the picked price for the insurance from the 2,000 shillings to complete the purchase.

4.2.4. Insurance products and payouts

The two insurance products were actuarially fair and identical in expected payout and premium (365 shilling given a compensation rate of 500 shillings per bag of maize lost). The SP product covered all losses attributable to drought only: farmers received compensation for losses of 1, 2, or 4 bags due to drought but received no payout for losses caused by pests and diseases. For example, a farmer who lost 2 bags due to drought under the SP product received a payout of KSh 1,000, while a farmer who lost 2 bags due to pests did not receive any payout.

The MP product, in contrast, covered major losses only (4 bags) from either drought or pests and diseases, or both. Under this product, farmers received no payout for minor losses (1 or 2 bags) from either risk but were compensated when experiencing major losses from one or both risks, thereby providing protection against rare catastrophic loss events. As a result, the two products differ in their exposure to tail risk, captured by the variance and skewness in yield, despite being equal in expected payout (see Appendix Table 4.1). In the third round of the game, payouts were subject to basis risk, such that farmers did not receive compensation following a loss when non-performance occurred.

4.2.5. Data, data collection, and balance

The data used in this analysis was collected in two rounds. The first round, conducted in December 2021 to January 2022 focused on farmer demographics (household size, farming experience, farm size, number of people earning income in the household, experience with other insurances, insurance literacy, financial literacy, risk taking, credit, risk aversion, main agricultural

risk, and main occupation), and information on locus of control. The second round, conducted in March and April 2022 focused on the WTP experiment and some behavioral factors, namely optimism bias and prudence. Part of the data from both rounds were used in Osiemo et al. (2025). The authors assessed the effect of game-based (experiential) learning and the conventional narrative-based on knowledge outcomes and demand for actual insurance. This paper addresses a unique gap in literature. Our two main outcome variables in this paper are the WTP (the amount a farmer bid for a product) and whether the farmer wanted to switch to an alternative product. We present summaries of the data and balance in Table 4.1.

On average, farmers assigned to the SP and MP arms were balanced across observable characteristics, except for farm size and gender. The average household size is 5 members, while the average farming experience was 23 years, indicating a relatively older farming population; a majority (83%) of the farmers were over 35 years old. Average landholdings were about 3 acres, which is close to the national average for small-scale farmers of about 2 acres (Birch, 2018). Based on the parameters from Tanaka et al. (2014), the average risk aversion in our sample was 0.55 which is comparable to other studies that focus on small-scale farmers (see for example Bocquého et al., 2014). The average locus-of-control score was positive (mean = 8), indicating that farmers generally believe their actions influence outcomes. Optimism bias was also positive (mean = 18), suggesting that farmers overestimated their probability of favorable outcomes in the experimental lottery. Women constituted 55 percent of the sample, consistent with evidence of substantial female participation in agricultural production (Diiro et al., 2018). Educational attainment was low: only 38 percent of farmers had completed education beyond the primary level.

Table 4.1: Descriptive summaries and balance check

Variable	Overall			Multiple peril (MP)			Single peril (SP)			MP vs. SP
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	P-value
Continuous variables										
Household size	334	5.20	2.50	162	5.20	2.50	172	5.20	2.40	0.959
Farming experience	334	23.00	14.00	162	23.00	15.00	172	23.00	13.00	0.971
Farm size	334	3.30	4.20	162	2.90	2.70	172	3.70	5.20	**0.063**
Proportion of people earning income in the household	334	2.40	1.10	162	2.30	1.20	172	2.50	1.00	0.292
Experience with other insurances	334	2.00	1.90	162	2.00	2.00	172	2.10	1.80	0.682
Wealth quintile	331	3.60	1.00	160	3.70	0.96	171	3.60	1.00	0.580
Insurance literacy	334	3.10	1.10	162	3.10	1.10	172	3.20	1.00	0.217
Financial literacy	334	2.80	0.79	162	2.80	0.80	172	2.70	0.77	0.216
Risk taking	334	33.00	4.30	162	33.00	4.40	172	32.00	4.20	0.644
Access to credit	334	1.10	0.34	162	1.10	0.33	172	1.10	0.35	0.632
Risk aversion	334	0.55	0.50	162	0.53	0.50	172	0.57	0.51	0.471
Locus of control	334	8.00	5.30	162	7.60	5.00	172	8.40	5.60	0.162
Optimism bias	334	18.00	11.00	162	18.00	11.00	172	17.00	11.00	0.749
Prudence	334	3.20	1.50	162	3.20	1.60	172	3.20	1.50	0.643
Categorical variables										
Farmer uses improved seed variety	334	0.74	0.44	162	0.72	0.45	172	0.77	0.42	0.284
Important risk	334	0.69	0.46	162	0.67	0.47	172	0.72	0.45	0.403
Agriculture as main occupation	334	0.74	0.44	162	0.72	0.45	172	0.76	0.43	0.566
Farmer is male	334	0.45	0.50	162	0.40	0.49	172	0.49	0.50	**0.088**

Above 35 years old	334	0.83	0.38	162	0.81	0.39	172	0.85	0.36	0.331
Above primary education	334	0.38	0.49	162	0.35	0.48	172	0.41	0.49	0.355

Note: Values for categorical variables are percentages. The p-values were calculated using the xbalance function in the R language

4.3. Empirical approach

We use an OLS regression framework as our main specification to test the first hypothesis (there is no difference in WTP for the SP and MP products). The specification is as in equation (E.4.1).

$$WTP_i = \beta_0 + \beta_1 Product_{ij} + \beta_2 X_i + \varepsilon_i \quad \text{(E.4.1)}$$

WTP_i is the amount in Kenyan shillings individual *i* bid for an insurance product, while $Product_{ij}$ is a dummy for the product assigned to an individual *i* (1 = MP product and 0 otherwise). X_i denotes control variables, while ε_i is an error term. We test whether the null hypothesis $\beta_1 = 0$, which implies that there is no difference in the WTP for the SP and the MP products.

To test the second hypothesis—the effect of non-performance on willingness to pay—we estimate three specifications. Because each farmer values the same product twice (first without non-performance and subsequently with a positive probability of non-performance), we exploit the panel structure of the data. We compare fixed-effects and mixed-effects specifications as a robustness check. The mixed-effects model, specified in equation (E.4.2), explicitly accounts for unobserved individual heterogeneity through random effects, while the fixed-effects specification in equation (E.4.3) controls for time-invariant individual characteristics, thereby identifying the effect of non-performance from within-farmer variation.

$$WTP_{ir} = \delta_0 + \delta_1 Nonperformance_{ij} + \delta_2 X_i + \mu_i + \varepsilon_{ir} \quad \text{(E.4.2)}$$

$$WTP_{ir} = \delta_1 Nonperformance_{ij} + \alpha_i + \varepsilon_i \quad \text{(E.4.3)}$$

As in (E.4.4), WTP_i denotes the amount in Kenyan shillings individual i bid for the insurance product in round r. $Nonperformance_{ij}$ denotes the chance of non-performance for product j for individual i (either 0, 5%, 10%, or 15%). X_i is as in equation (E.4.1). The error term in (E.4.3) is decomposed into two components: μ_i captures time-invariant, individual-specific unobserved heterogeneity, while ε_{ir} captures random, round-specific variation in WTP. The two components are assumed to be mutually independent and orthogonal to the regressors X_i. Our parameter of interest is δ_1; testing $\delta_1 = 0$ corresponds to assessing whether non-performance affects WTP.

4.4. Results and discussion

4.4.1. WTP for SP and MP products

The overall average bidding price for the insurance products was Ksh. 1215 (Table 4.2). The WTP for the SP product was slightly higher (Ksh. 1223) compared to that of the MP product (Ksh. 1207). The difference between the WTP for the MP and SP products was not statistically significant from a t-test (p-value = 0.769).

Table 4.2: Summary of WTP

	Overall			Multiple peril (MP)			Single peril (SP)			MP vs. SP
	N	Mean	SD	N	Mean	SD	N	Mean	SD	P-value
Average WTP (no basis risk scenario)	334	1215.00	487.00	162	1207.00	490.00	172	1223.00	485.00	0.769

Note: SD is standard deviation.

We next examine the demand curves for both products (Figure 4.2). As expected, the share of farmers purchasing insurance declines with price for both products. The demand curves are indistinguishable, which is consistent with the fact that the two products are actuarially identical, with equal expected payouts and premiums.

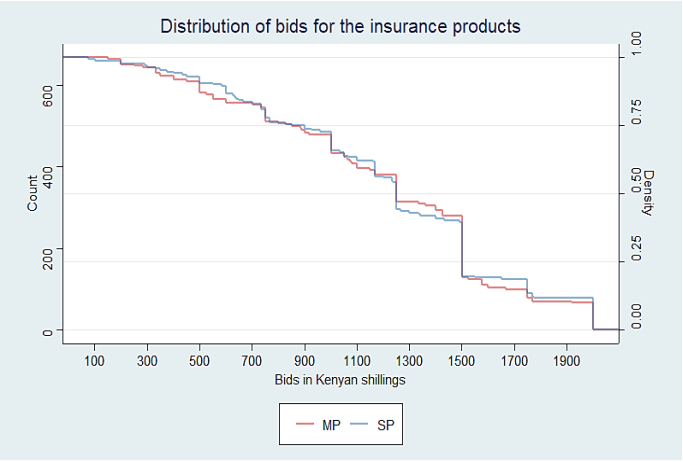


Figure 4.2: Demand for SP and MP insurance products

However, when given the opportunity to switch products, 61 percent of the farmers in the SP arm wanted to switch to the MP product while only 37 percent of those in the MP arm wanted to switch to the SP product (see Figure 4.3). Thus, preference for the MP product becomes clear only at the second stage of elicitation. WTP, even though incentive compatible gives a different result, and the choice task gives another result. This raises a central question: does the preference reversal reflect noise ("irrational choice") or measurement error in WTP elicitation, or does it instead reflect underlying preferences that are not captured in WTP even when the elicitation is incentive-compatible? In the sections that follow, we examine both issues.

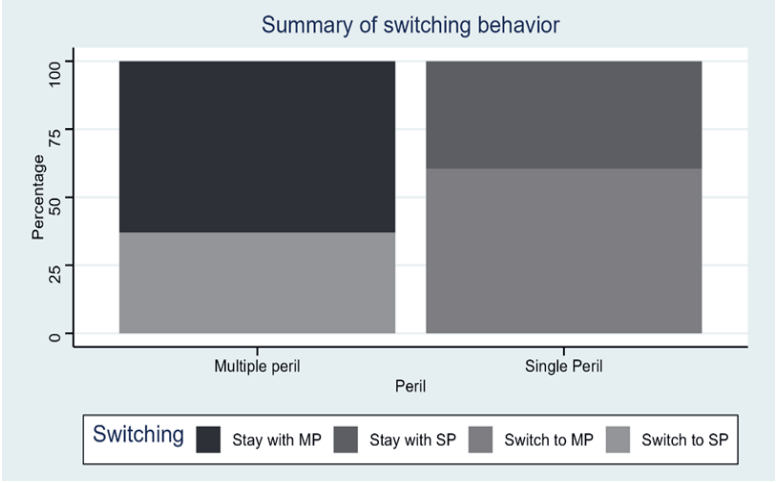


Figure 4.3: Farmer product switching behavior

4.4.2. Regression analysis of WTP for SP and MP products

First, we estimate regression models to move beyond simple comparisons of mean WTP and demand curves. Table 4.3 reports the results. Models (1) and (2) estimate elicited WTP using OLS, while models (3) and (4) examine switching behavior using a probit specification and report marginal effects. Model (1), equivalent to a two-sample t-test, indicates no statistically significant difference in WTP between the SP and MP products. This result remains unchanged after including covariates in model (2).

In contrast, models (3) and (4) reveal a different pattern. Farmers initially assigned to the MP product are significantly less likely to switch than those assigned to the SP product, consistent with the descriptive evidence presented earlier. Reported reasons for switching point to the role of subjective risk perceptions. Many farmers who switch to the MP product state that both drought and pests are important risks and that coverage against both is therefore preferable (Figure 4.4). By contrast, farmers who switch to the SP product emphasize that drought is the more severe and less controllable risk, making full coverage against drought losses particularly attractive. While

these reported reasons could be interpreted as post-switching rationalization, evidence from machine learning analyses of switching behavior indicates that pre-intervention risk perceptions, and prior shock experiences are strong predictors of switching (see Appendix 4.E). This pattern is consistent with the view that underlying beliefs and experiences, rather than purely ex post justification, contribute to the observed preference shifts.

In addition to the role of subjective risk perceptions, it is important to note that although the two products are identical in expected payouts and premiums, the MP contract weakly dominates the SP contract in higher moments of the payout distribution, exhibiting lower variance and slight positive skewness. Therefore, the MP is attractive to farmers who portray precautionary behavior such as prudence. Prudence is one of the key features predicting switching behavior (see Appendix 4.E).

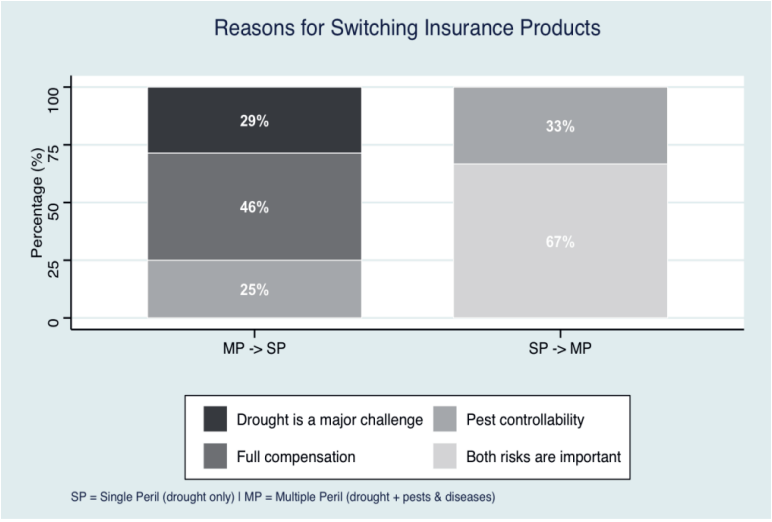


Figure 4.4: Reasons for switching

Taken together, these findings are consistent with context-dependent preferences (Hoeffler & Ariely, 1999), whereby preferences are shaped by the decision environment rather than fully

predetermined (Ariely et al., 2003). While equality in WTP across SP and MP is consistent with risk-neutral valuation at the level of expected payouts, switching behavior reveals preferences shaped by subjective risk perceptions and sensitivity to tail risk. The observed switching patterns therefore seem to reflect systematic preferences rather than random or irrational choice.

Table 4.3: Effect of product type on WTP and switching behavior

	(1)	(2)	(3)	(4)
Multiple Peril	0.075	0.111	−0.603***	−0.619***
	(0.071)	(0.076)	(0.145)	(0.153)
Additional controls	No	Yes	No	Yes
Number of observations	334	331	334	331
R2	0.306	0.358		
AIC	427.5	431.9	466.2	483.8
Log likelihood			−422.105	−413.968

Note: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Additional controls include gender, household size, farming experience, farming plus other occupations, primary education and below, farm size, proportion of people earning income in a household, wealth quintile, financial literacy, insurance literacy, risk taking, risk aversion, locus of control, optimism bias, and prudence. Standard errors are robust, clustered at sublocation level.

Having established that the observed preference reversal is systematic, we next assess whether WTP behaves in ways consistent with theory and prior empirical evidence, to rule out elicitation noise as the primary driver of the reversal. We focus on two dimensions. First, we test whether WTP responds to variation in product quality, proxied by non-performance (basis risk). Specifically, we compare WTP for each product with and without non-performance. Failure to observe a negative relationship would cast doubt on the validity of the elicited valuations. Second, we assess the sensitivity of WTP to the elicitation mechanism by comparing valuations obtained using the BDM and TIOLI procedures. Systematic differences across mechanisms would suggest

measurement artifacts rather than preference-based explanations. Passing these tests therefore strengthens the interpretation that the observed preference reversal reflects underlying preferences rather than noise in valuation.

4.4.3. Is WTP sensitive to non-performance

In Figure 4.5, we compare the demand curves for the products with and without non-performance. As in the scenario without non-performance, WTP declines with price, consistent with downward-sloping demand. Importantly, WTP under basis risk is consistently lower than WTP in the absence of basis risk as expected (see Appendix 4.D for detailed results on sensitivity to non-performance for the MP and SP products).

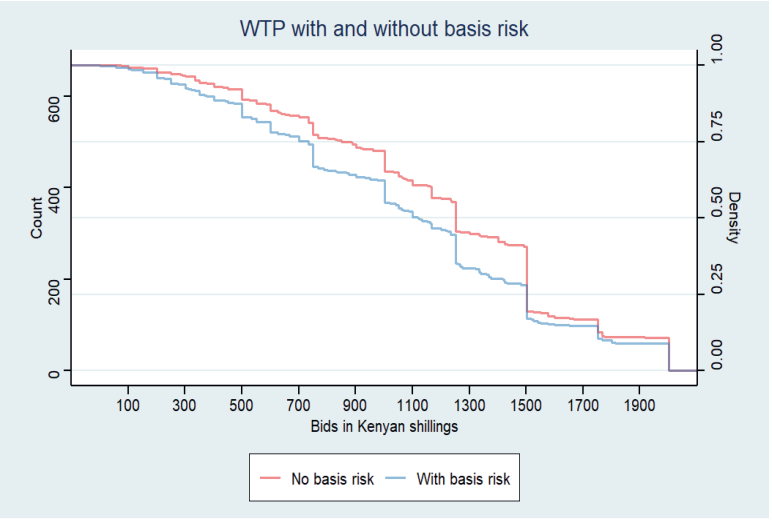


Figure 4.5: WTP, with and without basis risk

Next, we assess the causal effect of product non-performance on WTP using a regression framework (Table 4.4). All models in Panel A are estimated using mixed-effects specification. Models (1) uses the full sample, while models (2) and (3) restrict the sample to the SP and MP group respectively. Across all models, non-performance is strongly and negatively associated with WTP, consistent with existing evidence that basis risk reduces demand for index insurance (Clarke,

2016; Hill et al., 2016; Lichtenberg & Martinez, 2022). The results are unchanged under a fixed-effects specification (Panel B), confirming robustness to model specification. While the estimated effect of non-performance appears slightly larger for the MP product, a t-test indicates that the difference between the SP and MP coefficients is not statistically significant. If the WTP reported by the farmers was noisy, then we couldn't observe the systematic reduction in WTP to variation in product quality.

Table 4.4: Sensitivity of WTP to non-performance

	(1)	(2)	(3)
Panel A (Mixed effects specification)			
Non-performance	-1.432***	-1.014***	-1.839***
	(0.267)	(0.292)	(0.452)
Number of observations	662	342	320
AIC	1248.7	576.2	735.3
Additional controls	Yes	Yes	Yes
Panel B (Fixed effects specification)			
Non-performance	-1.403***	-0.943***	-1.871***
	(0.290)	(0.313)	(0.475)
Number of observations	668	344	324
R^2	0.825	0.869	0.796
AIC	830.7	251.5	515.0

Note: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Additional controls in Panel A include gender, household size, farming experience, farming plus other occupations, primary education and below, farm size, proportion of people earning income in a household, wealth quintile, financial literacy, insurance literacy, risk taking, risk aversion, locus of control, optimism bias, and prudence. Standard errors are robust, clustered at sublocation level.

4.4.4. Is WTP sensitive to elicitation mechanism

Next, we assess the sensitivity of WTP to the elicitation mechanism using a regression framework. As shown in Table 4.5, the elicitation method does not have a statistically significant effect on WTP. This finding is consistent with Cole et al. (2020), who report no systematic differences in WTP across elicitation mechanisms for an agricultural information service, though

they document mixed evidence in the context of index insurance. In contrast, Berry et al. (2020) find significantly lower valuations under BDM relative to TIOLI. Insensitivity of the WTP to elicitation mechanism enhances confidence in our findings.

Table 4.5: Sensitivity of WTP to elicitation mechanism

	(1)	(2)	(3)	(4)	(5)	(6)
TIOLI	-0.024	-0.027	-0.024	-0.027	-0.025	-0.029
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Single Peril			-0.004	-0.004	-0.004	-0.003
			(0.019)	(0.019)	(0.019)	(0.019)
Additional controls	No	Yes	No	Yes	No	Yes
Number of observations	667	663	667	663	667	663
Log likelihood	-161.339	-147.466	-161.312	-147.448	-160.998	-147.134

Significance: *** = $p < 0.01$; ** = $p < 0.05$; * = $p < 0.1$. Control variables in the regressions are sex, household size, farming experience, farm size, use of improved variety, number of people earning income in a household, experience with other insurances, wealth quintile, insurance literacy, financial literacy, random price, random price squared, risk aversion, locus of control, optimism bias, and prudence.

4.5. Discussions and conclusion

Willingness to pay (WTP) is widely used to gauge demand for agricultural innovations and plays a central role in their design, pricing, and targeting. Standard valuation approaches elicit WTP by presenting individuals with a single product and asking them to value it through auctions or other elicitation mechanisms (Canavari et al., 2019). These approaches implicitly assume that preferences are well defined, internally consistent, and fully revealed by stated prices. However, there is limited evidence on whether WTP alone recovers context-dependent preferences, particularly when products differ along complex dimensions such as exposure to tail risk.

This paper addresses this gap by examining whether WTP fully captures farmers' preferences over index insurance products that are actuarially identical in expected payout and premium but differ in their exposure to catastrophic losses. Using a framed experiment, we

implement a two-stage elicitation design. In the first stage, we elicit WTP for a single-peril (SP) and a multiple-peril (MP) index insurance product using a Becker–DeGroot–Marschak (BDM) mechanism embedded in a game. In the second stage, we observe switching behavior when farmers are subsequently exposed to the alternative product (i.e., those initially assigned to the MP product are offered the SP product, and vice versa). We complement this design with validation tests that assess whether WTP responds systematically to economically meaningful variation in product quality—captured by non-performance (basis risk)—and whether it is sensitive to the elicitation mechanism (BDM versus TIOLI). Together, these tests allow us to rule out elicitation noise as the primary driver of observed behavior.

We find that average WTP for the SP and MP products is statistically indistinguishable, consistent with their identical expected payouts and premiums. Interpreted within an expected utility framework, this pattern is suggestive of risk-neutral valuation at the level of mean payouts. However, switching behavior reveals a markedly different pattern. When given the opportunity to choose, a substantial share of farmers initially assigned to the SP product switch to the MP product, whereas relatively few switch in the opposite direction. Farmers who switch from the SP to the MP product frequently report that both drought and pests constitute important risks and that protection against multiple shocks is therefore valuable. In contrast, those who switch toward the SP product emphasize that drought is more severe and less controllable than pests, rendering full coverage against drought losses particularly attractive. These reported reasons are unlikely to reflect mere post-switch rationalization; rather, they align with pre-intervention risk perceptions and prior exposure to shocks, suggesting that switching behavior is grounded in underlying heterogeneity in perceived risk profiles.

From a normative perspective, the preference reversal is not arbitrary. Although the two products are identical in expected value, the MP product weakly dominates the SP product in higher moments of the payout distribution, exhibiting lower variance and slightly positive skewness. Under a constant relative risk aversion (CRRA) framework, a Taylor expansion of expected utility implies that such differences increase expected utility, providing a rational basis for preferring the MP product. The remaining "puzzle" is why this ranking does not manifest in WTP.

We rule out the possibility that the preference reversal is driven by elicitation noise. First, the use of an incentive-compatible mechanism with real monetary consequences mitigates hypothetical bias. Second, WTP responds negatively to non-performance in a manner consistent with prior evidence on basis risk and demand for index insurance: basis risk reduces demand (Clarke, 2016; Hill et al., 2016; Kramer et al., 2022; Lichtenberg & Martinez, 2022), and lastly, WTP is not systematically affected by the elicitation procedure.

These findings carry implications for both insurance design and valuation methods. From a product design and policy perspective, the results indicate that subjective risk perceptions play a central role in shaping demand for risk management instruments, particularly index insurance. This evidence underscores the importance of incorporating heterogeneity in farmers' risk profiles into product design, consistent with prior work emphasizing the value of flexible products tailored to farmers' heterogeneous demand (Ceballos & Robles, 2020).

The relative appeal of the MP product (from the switching behavior) suggests that protection against rare but catastrophic losses carries disproportionate value. At the same time, switching toward the SP product highlights the importance some farmers attach to insuring risks perceived as largely beyond their control. For these farmers, concentrating coverage on drought—

viewed as both more severe and less manageable than pests—appears to outweigh the benefits of diversified protection. Together, these patterns underscore that both tail risk and perceived controllability of risks are central to valuation and choice of index insurance products.

From a valuation perspective, our results suggest that WTP alone may obscure economically meaningful heterogeneity in preferences for index insurance products, particularly when insurance products differ in their exposure to tail risk and when subjective risk perceptions vary across farmers. Even when demand curves appear well behaved, stated prices may fail to capture the utility gains associated with eliminating low-probability catastrophic losses. This disconnect may help explain persistent adoption gaps of agricultural innovations despite apparently high ex-ante WTP. Linking valuation exercises with explicit choice-based validation offers a practical way to reconcile stated values with revealed preferences therefore improve the design, targeting, and promotion of agricultural innovations, and ultimately help address bottlenecks in adoption.

Several avenues for future research remain. First, although farmers' stated reasons for switching are consistent with their subjective risk perceptions, the underlying mechanisms driving the preference reversal remain unclear, a motivation for further investigation into the role of higher-order risk preferences, subjective beliefs, and behavioral responses. Second, we take a simplified view of risk and uncertainty and do not model interactions across risks and the order in which the risks occur that may affect multiple-peril payouts, which future work should consider. Future work should also examine whether protection against catastrophic losses across multiple risks encourages adoption of high-return but risky technologies and helps farmers escape risk-induced poverty traps, and how coverage levels for the MP product should vary across different risks and farmer typologies.

Appendix 4

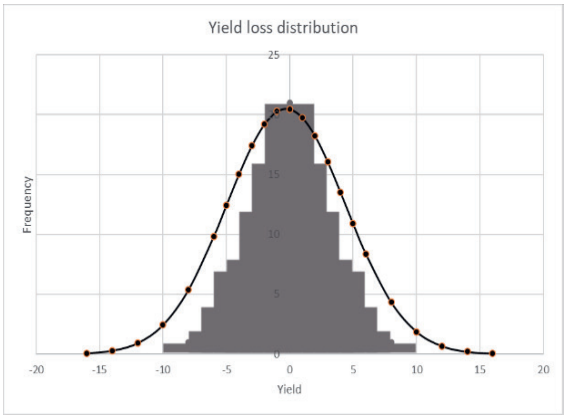
Appendix 4.A: Payout distributions of the SP and MP products

Column A of Appendix Table 4.1 shows losses (i.e., the number of bags lost from either drought or pests). Column 2 shows the amount a farmer received after experiencing a loss from drought if she was assigned to the SP product. Column 3 shows that amount a farmer received if she experienced major losses from both drought and pests. This distribution of yields as shown in Appendix Figure 4.1 were carefully selected to achieve a normal distribution: high probabilities for low to moderate losses (gains) and low probabilities for extreme outcomes.

Appendix Table 4.1*: Payout distributions for the SP and MP products*

Losses (of bags)	Single peril (SP)	Multiple peril (MP)
-4	2000	4000
-2	1000	0
-1	500	0
-1	500	0
0	0	0
0	0	0
0	0	0
1	0	0
1	0	0
2	0	0
4	0	0
Mean	**364**	**364**

The yield loss distributions were selected to achieve (close to) a normal distribution



Appendix Figure 4.1: Yield losses reflected a normal distribution

Appendix 4.B: WTP elicitation

Appendix 4.B.1: BDM elicitation without basis risk

We will play the game again as we did in round 1 (round 1 was a practice round to ensure that you understood the risk game), but in this case with crop insurance.

1. The product covers losses arising from XX (this varied based on whether the farmer was assigned the SP or MP product): farmers assigned to the SP product were notified that the insurance covered all losses from drought, while those in the MP product were notified that the insurance covered major losses only from either drought or pests, or both.
2. The insurance product will compensate you 500 game shillings for every bag of maize you lose.
3. We again give you 12,000 shillings of game currency to finance your production activities. Remember that your cost of production is 10,000 shillings and that, we offer

you a crop cover that compensates 500 shillings for every bag of maize you lose. You must buy the insurance at the beginning of the season.

4. You have 2,000 shillings, from which you can spend on crop insurance. Whether you purchase the insurance will depend on whether the price you pick from this bag (enumerator to show farmers the bag) is the same as the price you mention or less as I will explain later.
5. Let us now determine the price at which you will buy the insurance cover.
6. Step 1: What is the maximum amount of money will you be willing to pay for such an insurance product (enumerator to remind the farmer about the product). Remember that the cost is per acre of land (price 1).
7. Step 2: Suppose the insurance cover was offered to you at a slightly higher price than your mentioned price (price 1), how much would you pay for it (price 2)?
8. Step 3: Suppose the insurance cover was offered to you at a slightly higher price than price 2, how much would you be willing to pay for the cover?
9. Repeat this procedure until the farmer is not willing to change the price.
10. Now we will determine whether you will purchase the cover or not.
11. This bag (enumerator to show the third bag to the farmer) contains 3 pieces of paper with prices on them. I will ask you to draw one price (paper) from the bag.
12. If the price you draw is less than your maximum bidding, then you pay for the product at the price you draw from the bag. If the price you draw is higher, then you do not buy the insurance product.
13. Remember that your final revenue will be total revenue (number of bags multiplied by the price per bag) less production cost and the cost of insurance.

14. Once you have purchased (not purchased the insurance), we can now go ahead to produce maize again as we did in round one. The enumerator should take the farmer through the steps of yield determination as in round 1:
    a. Select a bead from bag A
    b. Again, select another bead from bag B
    c. Determine yield as in round 1
15. If you experience losses from drought (bag A), we compensate you 500 shillings at the end of the season, otherwise you do not get compensated.
16. Enter the amount of money the farmer should be compensated.

Appendix 4.B.2: BDM with basis risk (5%, 10%, 15%)

1. We will play the game again as we did earlier. However, you will not always receive compensation when you experience a loss because of many reasons including poor verification of losses, wrong entry of data or any other technical issues. We call this basis risk.
2. You must pick a green bead from a fourth bag as we explain in the next steps for you to get compensated.
3. Follow steps 2 to 14 as described earlier as follows:
    a. Remind the farmers that the insurance product compensates 500 shilling for every bag of maize lost because of drought.
    b. Determine the price at which the farmer will buy the insurance by:
    c. Asking the farmer her initial bidding price
    d. Ask again if the farmer is willing to buy the product at a slightly higher price

e. Repeat procedure of asking price as in above until the farmer is no longer willing to adjust her price

f. After determining the insurance price, proceed to determine the yield

g. Ask the farmer to select a bead from bag A

h. Ask the farmer again to select another bead from bag B

i. Determine the final yield as in round 1.

4. If you experience losses because of drought (jar A), we compensate you at the end of the season 500 shillings for every bag of maize lost. Remember that you will be compensated only if you select a green bead from this fourth bag.

5. The fourth bag contains 10 beads of which 9 to 10 are green (for the case of 5% basis risk).

6. Select a bead from the bag.

7. If you choose a green bead, then we compensate 500 shillings for every bag you lose, otherwise you do not get compensated.

8. Record the amount of money the farmer should be compensated.

Appendix 4.B.3: TIOLI elicitation without basis risk

1. We will play the game again as we did in round 1 (round 1 was a practice round to ensure that farmers understood the risk game), but in this case with crop insurance.
2. The product covers losses arising from XX (this varied based on whether the farmer was assigned the SP or MP product): farmers assigned to the SP product were informed that the insurance covered all losses from drought, while those in the MP product were

informed that the insurance covered major losses only from either drought or pests, or both.

3. The insurance product will compensate you 500 game shillings for every bag of maize you lose.
4. We again give you 12,000 shillings of game currency to finance your production activities. Remember that your cost of production is 10,000 shillings and that, we offer you a crop cover that compensates 500 shillings for every bag of maize you lose due to drought.
5. You must buy the insurance at the beginning of the season. You have 2,000 shillings, from which you can spend on crop insurance.
6. Let us now determine the price at which you will buy the product.
7. Bag C contains three pieces of paper each having a unique price on it.
8. The price at which you purchase the insurance will depend on the price you draw from the jar.
9. Pick one piece of paper from the bag (enumerator to note the price).
10. Will you buy the insurance at the price you drew (Yes/No)?
11. The enumerator should note the response of the farmer.

Appendix 4.B.4: TIOLI elicitation with basis risk (5%,10%, 15%)

1. We will play the game again as we did earlier. However, you will not always receive compensation when you incur a loss because of many reasons including poor verification of losses, wrong entry of data or any other technical issues. We call this basis risk.
2. In our game, you must pick a green bead from a fourth bag as we explain in the next steps for you to get compensated.

3. Follow steps 2 to 14 as in round 2:

a. Remind the farmers that the insurance product compensates 500 shillings for every bag of maize lost because of drought.

b. Determine the price at which the farmer will buy the insurance by:

c. Letting the farmer draw a price from the third bag.

d. Ask the farmer if she is willing to buy the insurance at the drawn price (Yes/No).

e. After determining the insurance price, proceed to determine the yield:

f. Ask the farmer to select a bead from bag A

g. Ask the farmer again to select another bead from bag B

h. Determine the final yield as in round 1.

4. If you experience losses from drought (bag A), we compensate you 500 shillings for every bag of maize you lose at the end of the season. Remember that you will be compensated only if you select a green bead from this fourth bag.
5. The fourth bag contains 10 beads of which 9 to 10 are green (for 5% basis risk).
6. Choose a bead from the bag.
7. If you choose a green bead, you will be compensated for the yield losses you experienced, otherwise you do not get compensated.
8. Enumerator to record the amount of money the farmer should be compensated.

Appendix 4.C: Switching questions (applied for both BDM and TIOLI groups)

1. Imagine you have a product that covers losses from both risks only if the losses are 4 bags (major) from each risk. This means that if you lose 4 bags because of drought, and 2 bags from pests and diseases, then you are only compensated 500 shillings for each of the 4 bags you lost because of drought. If you lose 4 bags from drought, and another 4 bags

from pests and diseases, then you are compensated for 8 bags (4000 shillings). If you lose 4 bags from pests and diseases and 2 from drought, you only get compensated for 4 bags lost due to pest and disease (2000 shillings).

2. If this product (the multiple peril) was offered to you at the same price as your maximum bidding price (enumerator to remind the farmer of her maximum bidding price), would you switch from product A to product B? (Yes/No)

Appendix 4.D. Higher moments for the SP and MP products

There are four states of the world namely no shock, drought only state, pest only state, and both drought and pest state all occurring with a probability of 0.25 (Appendix Table 4.2). The outcomes in the individual scenarios are shown in the following tables.

Appendix Table 4.2: Scenarios and associated probabilities

Scenario	Description	Probability
S1	No shock	0.25
S2	Drought only	0.25
S3	Pests only	0.25
S4	Drought + pests	0.25

Loss distributions S2 after insurance payout (pr = 0.25)

Appendix Table 4.3: Yield outcomes in scenario 2

Loss (L)	Probability	SP loss	MP loss
−4	1/11	0	0
−2	1/11	0	−2
−1	2/11	0	−1
0	3/11	0	0
1	2/11	1	1
2	1/11	2	2
4	1/11	4	4

Loss distributions S3 after insurance payout (pr = 0.25)

Appendix Table 4.4: Yield outcomes scenario 3

Loss (L)	Probability	SP loss	MP loss
−4	1/11	−4	0
−2	1/11	−2	−2
−1	2/11	−1	−1
0	3/11	0	0
1	2/11	1	1
2	1/11	2	2
4	1/11	4	4

Loss distributions S4 after insurance payout (pr = 0.25)

Appendix Table 9: Yield outcomes scenario 4

Loss (L)	Probability	SP loss	MP loss
−4	1/11	−4	0
−2	1/11	−2	−2
−1	2/11	−1	−1
0	3/11	0	0
1	2/11	1	1
2	1/11	2	2
4	1/11	4	4

Moments for the different scenarios SP

Appendix Table 4.6: Moments for the SP scenarios

Scenario	Mean	Variance	Skewness
S1	0.000	0.000	0.000
S2	0.727	1.471	1.756
S3	0.000	4.000	0.000
S4	0.727	5.471	0.245

Moments for the different scenarios MP

Appendix Table 4.7: Moments for the MP scenarios

Scenario	Mean	Variance	Skewness
S1	0.000	0.000	0.000
S2	0.364	2.413	0.837
S3	0.364	2.413	0.837
S4	0.727	4.826	0.592

Overall moments

Overall mean $(\mu) = \sum_{s=1}^{4} P(s)\,\mu_s$

$\mu^{SP} = 0.25(0 + 0.727 + 0 + 0.727) = \boxed{0.364}$

$\mu^{MP} = 0.25(0 + 0.364 + 0.364 + 0.727) = \boxed{0.364}$

Overall variance: Var(Y)=E[Var(Y|s)] +Var(E[Y|s])

Var (SP) = $0.25(0 + 1.471 + 4.000 + 5.471) = 2.735$

Var (MP) = $0.25(0 + 2.413 + 2.413 + 4.826) = 2.413$

Variance of scenario means:$\mathrm{Var}(\mu_s) = 0.083$

Hence:

$Var(Y^{SP}) = 2.818$
$Var(Y^{MP}) = 2.496$

Overall skewness: $(\gamma) = \frac{\mathrm{E}[(\mathrm{Y}-\mu)]^3}{\sigma^3}$

$\gamma^{SP} = 0.62$

$\gamma^{MP} = 0.88$

Summary of the moments

Appendix Table 4.8: Overall moments summaries for SP and MP

Moment	SP	MP
Mean	0.364	0.364
Variance	2.818	2.496
Skewness	0.62	0.88

Appendix 4.E: Second-order Taylor approximation

Expected utility can be approximated as:

$$\mathbb{E}[u(Y)] \approx u(\mu) + \frac{1}{2}u''(\mu)\,\sigma^2 + \frac{1}{6}u'''(\mu)\,\mu_3$$

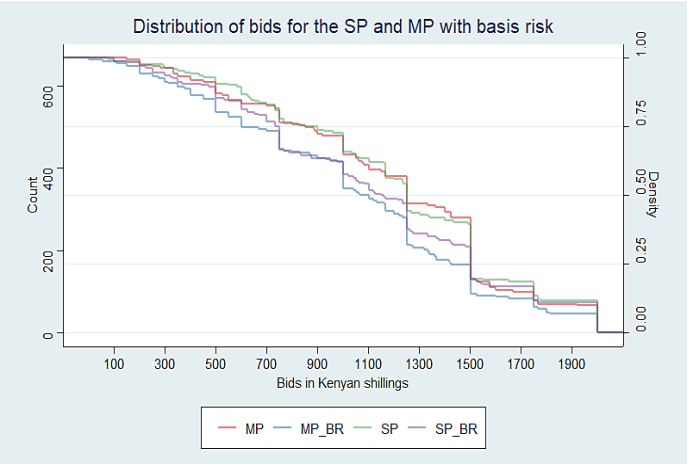
where: σ^2= variance, and μ_3= third central moment (skewness × σ^3). For a CRRA utility, $u''(\mu) < 0$ (variance hurts) and $u'''(\mu) > 0$ (positive skew helps). In this case MP gains twice since it has lower variance and higher positive skewness, thus the preference for the MP product is rational and justified.

Appendix 4.F: Features predicting switching behavior

Appendix Table 4.9: ML for features predicting switching

Feature/Variable	Importance (%)
Panel A: Switching from MP to SP	
Yield realizations in the game	100.000
Locus of control	45.293
Farming experience	44.266
Total harvest season prior to baseline	38.547
Maize farm size	26.257
Panel B: Switching from SP to MP	
Experienced drought season prior to baseline	100.000
Farming experience	93.935
Basis risk	91.033
Prudence	86.006
Youth	84.090
Experienced pests season prior to baseline	74.578
Financial literacy	65.954
Risk taking	65.808

Appendix 4.F: Sensitivity to non-performance for the individual SP and MP products



Appendix Figure 4.2: Effect of non-performance on WTP

Chapter 5

Experiential Learning, Narrative-Based Learning, and Insurance Adoption: Experimental Evidence from Kenya

Abstract

We compare the impact of two extension modalities on knowledge accumulation and willingness to pay for a weather index insurance product among smallholder farmers in Kenya. One approach to extension is based on experiential learning and involves participation in an incentivized framed experiment (or game). The other is based on conventional "narrative-based" learning. While both modalities increase farmer knowledge, incentivized gamification causes more learning. We also find that experiential learning affects follow-up demand for the insurance product, which is not true for narrative-based learning. Interestingly, demand for insurance shifts *inward* after playing the insurance game. This reduction in demand is mainly caused by increased knowledge about the insurance product, but we also present suggestive evidence that experiencing basis risk during the game was more salient than theory-based learning about basis risk. Game-based learning is an effective approach to promote knowledge accumulation and may accentuate or attenuate adoption of innovations by updating *ex-ante*, possibly biased, expectations.

Key words: Game-based; Learning; Incentive compatibility; Insurance; Extension; Information

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5.1. Introduction

A large gap exists between potential and actual crop yields in African smallholder farming. This partly explains why the region trails behind the rest of the world in terms of addressing hunger, malnutrition, and poverty (Tittonell & Giller, 2013). It is commonly believed that information transfers that promote the adoption of new technologies by smallholders are important in narrowing the yield gap (Aker, 2011). This includes information about modern technologies (e.g., Foster & Rosenzweig, 2010; Macours, 2019; Shiferaw et al., 2015; Takahashi et al., 2020)[5] and about how to manage production risk—particularly weather shocks (Burke & Emerick, 2016; Karlan et al., 2014). One approach for farmers to mitigate drought risks is adopting index-based weather insurance, but adoption rates of insurance products remain low across target populations (S. Cole et al., 2013; S. A. Cole & Xiong, 2017; Platteau et al., 2017). This may reflect complexity of the insurance product (Ahmed et al., 2020; Platteau et al., 2017). One may expect that addressing informational constraints would increase demand for index insurance. Farmers mostly receive information about new technologies, including insurance products, through agricultural extension services (Anderson & Feder, 2004, 2007; Cook et al., 2021). However, current approaches to extension are relatively ineffective (Bridle et al., 2020; Harou et al., 2022; Niu & Ragasa, 2018; Norton & Alwang, 2020). Since other information transfer modalities, such as social learning, are unable to close the information gap (Suri & Udry, 2022), there is a call for innovative approaches to provide extension to smallholders (Kaiser & Menkhoff, 2022).

[5] The literature on the effects of information transmission on adoption is still inconclusive. Some studies highlight the importance of trainings and extension (see Takahashi et al. (2020) for a review), but others find limited effects, especially when it comes to actual technology adoption and impacts (Harou et al., 2022; Leight et al., 2022; McKenzie, 2021). Kaiser & Menkhoff (2022) argue that one way to increase the efficacy of extension is finding alternatives to the conventional descriptive (lecture-based) information delivery. For instance, some studies focused on farmer-to-farmer technology extension, as more efficient extension strategies than traditional public-sector extension approaches (e.g., Nakano et al., 2018). Others consider the role of incentives in favoring dissemination of information through social learning (eg., Benyishay & Mobarak, 2019).

In this paper we evaluate the effectiveness of an alternative approach of extension, based on participation in an incentivized game which induces "experiential learning". The game focuses on risk and insurance and is played by a sample of Kenyan farmers. We evaluate how game-based learning affects knowledge about insurance as well as follow-up demand for a real-life index insurance product. Importantly, we compare the performance of experiential learning to the performance of a conventional (narrative-based) extension modality typically used by extension officers (Waddington et al., 2014).

Game-based learning entails the use of games for educational purposes (Dernat et al., 2023; Krath et al., 2021). Several theories on game-based learning and gamification are relevant in light of our study (see Krath et al., 2021), among which experiential learning theory (Kolb, 2015).[6] Experiential learning theory (ELT) provides a holistic perspective to learning and emphasizes the role of direct experience on learning, unlike cognitive learning theories that emphasize acquisition and recall of abstract symbols. Experiential learning theory is built around the concept of reflection—the subject experiences something (through doing), after which she reflects on these experiences and relates them to real life situations. The learner then forms generalizations (abstract concepts), which are applied to real life settings.

The education literature shows that game-based learning improves student learning outcomes (Bai et al., 2020). Games are effective because of their ability to illustrate goals and their relevance, they nudge users through guided paths, give users immediate feedback, reinforce good performance, and simplify content to manageable tasks (Landers et al., 2018; Plass et al., 2015).

[6] An alternative theory is self-determination theory (SDT), which is a theory of human motivation focusing on three needs: autonomy, competence, and relatedness (Deci & Ryan, 2008). Autonomy relates to volition, for example people engaging in a game out of their own choice. Competence relates to the desire to learn new skills and explore or understand the environment, while relatedness is about people's desire for social relations—which is especially relevant in multi-player games. Important elements are therefore motivation and engagement.

Games can mimic realities and induce reflection on experiences during the game—hence the label "experiential learning". Another advantage is that phenomena that usually can only be observed and experienced over a long period of time can be experienced within a relatively short time frame in a game. This is particularly important in agriculture where learning about new technologies, such as index insurance, tends to be complex and slow, because of the delay between decisions and outcomes and because performance depends on the interaction with other factors such as weather realizations (Bold et al., 2017). Finally, playing games can be "fun" so game-based learning may trigger intrinsic motivation and enable individuals to concentrate for longer, especially when dealing with topics that otherwise are less attractive (Plass et al., 2015).

A growing literature explores the potential role of game-based learning in helping farmers to learn about agricultural innovations (Elabed and Carter, 2015; Serfilippi et al. 2018; Klerkx, 2021). For example, Tjernström et al. (2021) examine how Kenyan farmers respond to an interactive app featuring a virtual farm that is calibrated to resemble their own farm. Participating farmers learn about the returns to different inputs. This is reflected in how they adjust real-life technology choices after the game. We are aware of three papers that study how experiential learning affects demand for crop insurance. These papers document that playing games has the potential to affect demand—shifting either knowledge, preferences or beliefs of farmers. Cai & Song (2017) play indemnity-based insurance games with rice farmers in China and find that experiences acquired in the game increase take-up. Jensen et al. (2018) use observational data to estimate basis risk of an index-based livestock insurance product in Kenya and examine how playing an insurance game interacted with actual basis risk increases knowledge and demand for

insurance. Finally, Janzen et al. (2021) show that game-based learning improves knowledge and increases demand for index insurance among smallholders in Kenya.[7]

We contribute to the literature as follows. Our focus differs from Cai & Song (2017) because we consider basis risk—the possible mismatch between farm level losses and those measured by the index—as a determinant of insurance adoption. Cai & Song (2017) consider indemnity-based insurance where basis risk does not exist. We randomly vary exposure to basis risk in our game, setting the paper apart from Jensen et al. (2018) who use observational data to study how realized basis risk affects purchase of index-based livestock insurance.[8] Our paper is closest to Janzen et al. (2021), who provide a basic (narrative-based) training to *all* participating farmers and then invite a random subsample of these subjects to also engage in experiential learning. Instead, we randomly assign our subjects to either a conventional narrative-based extension session *or* a game-based learning experience (or a control group), enabling us to isolate the game effect. We also use a binding auction to measure demand in an incentive-compatible fashion and do not rely on stated preferences. Finally, we use mediation analysis to probe the pathways through which the game influences outcomes.

We obtain three main results. First, while both game-based learning and narrative-style learning increase farmers' knowledge about index insurance, we find that game-based learning significantly outperforms the conventional narrative-based approach by around 0.15 SD. The finding that experiential learning fosters greater knowledge accumulation is consistent with Cai & Song (2017), Janzen et al., (2021) and others, but is in contrast with other studies (e.g., Gaurav et

[7] Other applications include teaching farmers about natural resource management (for example Assefa et al., 2021), teaching farmers on the trade-offs and synergies in livestock production systems (Dernat et al., 2023), ground-water management (Meinzen-Dick et al., 2018), and agroforestry management (Sari et al., 2024).
[8] Janzen et al. (2021) discuss how this may introduce endogeneity challenges.

al., 2011; Tessema et al., 2021). Compared to these latter studies, differences may arise because we used a game where subjects could earn money, depending on their choices in the game. Second, game-based learning shifts demand for the insurance product, but narrative-style learning does not. Perhaps surprisingly to readers who believe that "lack of knowledge" is an impediment to adoption, we find that the impact of experiential learning on adoption is negative—shifting demand inward. Third, the mechanism explaining the reduction in demand is twofold. Game-based learning fosters an improved understanding of the insurance product, which seems to underperform relative to *ex ante* expectations. This does not explain the full effect. Game-based learning also increases the *salience* of basis risk, and subjects exposed to "high basis risk scenarios" in the experiment lose their appetite for index insurance. In other words, the game corrects an overly optimistic image of insurance and creates more realistic expectations, and also enables farmers to experience the adverse effects of basis risk. Games designed to engender more informed choices about innovations may therefore discourage adoption. This underscores the need to address basis risk in index insurance products.

The remainder of this paper is organized as follows. In the next section, we describe the context, experiment design, and data. Section 3 presents the empirical estimation strategy. Section 4 summarizes the empirical results. Section 5 concludes.

5.2. Context, experiment design, and data

5.2.1. Context

Agriculture in Kenya is largely rainfed, and performance varies with weather outcomes. During the period 1980–2010, Kenya experienced 13 droughts, resulting in average annual losses of 155 million dollars (D'alessandro et al., 2015). Exposure to climate risks varies from county to county. We conducted our study in Meru County, one of the semi-arid counties in the Mt. Kenya

region. Meru County has seen a decline in economic growth in recent years, following the export ban of *miraa* (Khat) – a major cash crop produced locally (Carrier & Klantschnig, 2018). Farmers have switched to other crops, such as maize. Crop insurance could cushion farmers from some of the risks they suffer, especially droughts (Muriithi et al., 2022), but uptake of unsubsidized crop insurance products is low (Bulte et al., 2019).

According to discussions with farmers in the county, uptake is low due to various reasons including unclear terms of insurance policies, negative experiences with existing insurance products (including basis risk), opaque loss verification procedures, and long delays in processing claims. Poor understanding of how insurance works is a major barrier to adoption (Muriithi et al., 2022), and many farmers view crop insurance as an investment that should deliver a return (payout) at the end of the season. Enhancing farmers' understanding of crop insurance as a risk management strategy may increase relevance and shift demand for insurance products (Shin et al., 2022).

5.2.2. Sample selection, experimental design and the experiential learning intervention

Our pool of farmers consists of 1,409 farmers who earlier engaged in a household survey for the Innovation for Africa Climate Risk Insurance project conducted in late 2021 and early 2022. In the first sampling stage, we randomly sampled 84 sub-locations proportionate to the number of farmers from each of the nine sub-counties ("wards") of Meru County. The selection aimed to capture variation in maize production systems across wards. We randomly assigned individual farmers to treatment arms. Half of them were assigned to the game treatment (n_1=700) and the other half to the narrative treatment (n_2=350) or control group (n_3=350) (see experimental design in Figure 5.1). We block on sub-locations, the smallest administrative unit in Kenya, N = 84, assigning farmers from each block to the three experimental arms in equal proportions to promote

balance.[9] Farmers assigned to the game treatment were subsequently randomly assigned to one of three basis risk levels during the game they played: 5%, 10%, and 15%.

Farmers in the control group did not receive any information from us about crop insurance. We only mentioned crop insurance during the survey used to assess farmer knowledge about insurance. Farmers in the control group were informed that we wanted to measure their understanding of how index-insurance works. After a few warm-up questions, including an optimism bias exercise, we asked them 15 knowledge questions to test their understanding of crop insurance (see below). After this exercise, farmers were given an opportunity to ask questions about index insurance.

Next, we turn to our treatment arms. Interventions were implemented at the farmers' homes between March and April 2022.[10] Farmers were informed one week before the day of the experiment. Enumerators were randomly assigned to farmers and received strict instructions to stick to the script. When an enumerator arrived at the farmer's home, he/she introduced him/herself and explained the purpose of the visit. Importantly, participants assigned to the *Game* and the *Narrative* treatments received identical information about index insurance—the content of the narrative was "worked into" the game instructions.

[9] From our power calculations, we needed about 100 "blocks" with an "inter-cluster correlation" of 0.1, each block with 16 farmers to attain an effect size of 0.25. Using the same assumptions, the 84 blocks gave us a power of 0.8.
[10] This coincided with the main planting season in the region. However, because of logistical challenges, we did not offer the farmers the insurance product then but rather promised to offer the product in the coming cropping season.

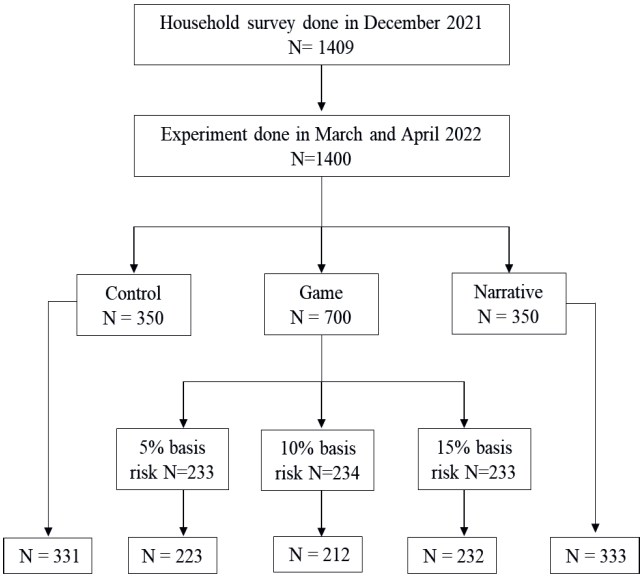


Figure 5.1: Experimental design

Note: The figures at the bottom are the number of farmers who participated in the experiment in each group, in total 1331 farmers.

Farmers assigned to the Narrative arm were informed that the training would take 30 minutes, that the aim of the exercise was to learn about how index insurance works, and that they could drop out at any point of the exercise without any repercussions. After participating in the incentivized game to measure optimism bias, farmers were taught about index insurance. They received the same information as those who played the game. The only difference is that information for the game group was crafted into learning activities that fostered "experience", while the information for the narrative group was delivered through the conventional "lecturing" way. The execution of the game took longer than the narrative session (90 minutes versus 30

minutes), which potentially is a confounding factor.[11] The information provided to the narrative group included details on crop insurance, types of insurance and types of risks covered by insurance products, insurance premiums, payout conditions, and the concept of basis risk. Details on the information that was provided to the farmers can be found in Appendix 5.3.

For farmers assigned to the Game arm, the enumerator explained that the game involved maize production on a hypothetical farm (incurring production costs, experiencing some risks, and getting a harvest at the end of the season) and index-insurance. Enumerators informed farmers that the objective of the game was to help them understand how index-insurance works, that the whole exercise would take not more than 90 minutes, and that the game provided an opportunity to earn some money (it was incentive compatible). Before the game started, farmers played an incentivized game to gauge optimism bias (see details in Appendix 5.1). Then the enumerator read the game instructions to the farmer and explained each of the instructions until the farmer fully understood them. We asked specific follow-up questions to test whether farmers understood every step of the game.

In the game, farmers produced maize on a hypothetical farm—a 1-acre piece of land. The farmer incurred production costs, experienced production risks, had the option to purchase insurance to cushion herself from these risks, and earned revenues from production. We considered two risks that were most frequently cited during the household survey: unreliable rainfall (drought) and pests or diseases. Next, farmers were endowed with 12,000 game shillings to cover production costs, where 100 game shillings were equivalent to 1 Kenyan shilling at the time of payout. Each bag of maize could be sold for 2,000 game shillings. After playing a practice round, farmers played

[11] Farmers were always free to "drop out" of the game if they got tired or bored. This never happened, so we assume that prolonged duration of the game was offset by its "fun" aspect. Farmers remained focused and interested during the game.

three "real" rounds. Round 1 was a repeat of the practice round, involving production without insurance. Round 2 introduced farmers with the opportunity to purchase crop insurance to mitigate production risk. Round 3 introduced basis risk for the insurance product (which we exogenously varied across farmers—see below). Afterwards, one of the rounds was randomly selected for actual payout. We now turn to the details of the game rounds.

Round 1: Yield realizations

The average yield in the game was 12 bags of maize, roughly the median yield in the study area. Yields varied depending on random drought and pest conditions. To determine how yields were affected by droughts, we offered farmers a jar (Jar A) with 11 beads. Each bead had one of the following numbers written on it: -4, -2, -1, -1, 0, 0, 0, +1, +1, +2, and +4.[12] These numbers represent *deviations* from the average yield. The farmer was asked to pick a bead from the jar. We repeated this procedure to determine yield deviations due to pests. We offered the farmer a second jar (Jar B) containing 11 beads with the same numbers. The farmer picked a bead from this jar as well. His or her yield in this round is simply the average yield (12 bags) plus the sum of the two beads. For example, if a farmer picked bead number -2 from Jar A and number -4 from Jar B, her realized yield would be 12-4-2=6 bags. Under the most favorable production conditions (no drought and no pests) farmers obtained a maximum yield of 20 bags of maize (12+4+4). In the worst-case scenario, they obtained only 4 bags of maize (12-4-4). These values are in line with evidence from discussions with farmers about harvests locally perceived as very good or very poor. The resulting distribution of yields approximately followed a normal distribution, as shown in Appendix Figure 5.1. The cost of production on this piece of land was game shillings 10,000.[13]

[12] We select these numbers to achieve a near normal distribution of yield realizations.
[13] Smallholder farmers spend about 10,000 shillings on land preparation, planting, buying seed, and planting fertilizer (e.g. Kirimi et al., 2018).

Deducting these production costs from the endowment resulted in a bonus of 2000 shillings (12,000–10,000) which we introduced to minimize the "house money effect" in subsequent rounds.

Round 2: Yield realizations with crop insurance

In Round 2 farmers had the option to purchase crop insurance to mitigate production risk. In the game yields vary with drought and pest realizations. Participants were randomly assigned to one of two actuarially identical insurance products, namely "single peril" (covering drought shocks only) or "multiple peril" (covering both shocks). The insurance product mimicked a hybrid insurance product where farmers receive a payout if their realized yield was below the region's average of 12 bags. For each bag below the average, if this was caused by drought, farmers in the "single peril" insurance received Ksh. 500. Those in the "multiple peril" insurance received Ksh. 500 only if the negative deviations from the average were major (either 4 bags because of drought, or 4 bags from pests or diseases, or both), regardless of their cause (drought or pest)[14]. This variation ensured that both products were actuarially identical. The main difference between the two is that in one case the insurance covered all types of negative shocks, whilst in the other it only covered one type of shocks (drought).[15] In what follows we pool data across these sub-arms.

We used a BDM approach to auction off the insurance product in the game. After receiving instructions, farmers stated a bid for the assigned insurance product and were asked to pick a (random) strike price from a jar with numbers (Jar C). If the bid was higher than the strike price, then the farmer purchased insurance at the strike price, else the farmer could not buy the insurance

[14] This meant that a farmer in the "multiple peril" insurance did not receive any payout if the deviations from the mean were not major (-1 or -2 bags of maize).
[15] The rationale behind introducing this variation was to test if it would be confounded with non-performance and thus lead to a lower valuation for the insurance that excluded completely one type of shocks. We do not find such difference in valuations, indicating that participants on average assigned a similar value to these actuarially similar products, which we treat as one throughout the rest of this paper.

product. Revenues in Round 2, therefore, are the sum of realized yield (multiplied by the unit price of maize) and possible insurance payouts for farmers who bought insurance and suffered losses, minus the cost of production and possibly the cost of insurance.

Round 3: Yield realizations with crop insurance and basis risk

Before starting this round, we demonstrated the concept of basis risk to the farmer. We only focused on *negative* basis risk, exactly like we did in the narrative-based extension arm. Excluding positive basis risk may have consequences for how farmers value the insurance product as the beneficial effects of positive basis risk may attenuate the adverse effects of negative basis risk. Shin et al. (2022) show that under cumulative prospect theory, positive basis risk will increase demand. However, if insurance is a financial product that is first and foremost supposed to transfer resources from good to bad states, positive basis risk may have similar negative effects on demand as negative basis risk (as found for instance by Vosper & Cecchi, 2023). Since we were underpowered to have a separate treatment arm to study the impact of positive basis risk, we present a simplified experiment (and narrative) that only features negative basis risk.

We used a jar with 10 beads (Jar D), blue and green, to illustrate basis risk. Drawing a blue bead implies that the farmer does not receive a payout, even if she suffered a production loss. We varied the number of blue beads in Jar D across farmers to vary exposure to basis risk. We use three levels of basis risk: 5%, 10%, and 15%. For the 5% basis risk scenario, we included either 9 or 10 green beads (1 or 0 blue beads), with equal probabilities. The farmer did not know the exact number of blue beads in the jar.[16] The probability of receiving a payout for the farmer was 95% (i.e., a 5% chance of not receiving a payout). Similarly, for the 10% basis risk scenario we included

[16] We use either 9 or 10 blue beads to (1 or 2 green beads) to achieve an average of 5% basis risk (1 - (9/10 + 10/10)/2).

8 to 10 green beads in the jar (equal probabilities), and for the 15% basis risk scenario we included 7 to 10 green beads in the jar.[17] The aim of the exercise was to demonstrate that basis risk is a probabilistic event with ambiguous probability and to foster learning by "doing" (experiencing the basis risk outcome).

In Round 3, farmers decided to purchase insurance or not (as in Round 2) and determined their yield outcomes (as in round 2). Next, they determined their realization with respect to basis risk**.** Farmers who did not purchase insurance, because they bid below the strike price in the BDM auction, also took part in the basis risk exercise—they learned what would have happened had they been covered by insurance, but did not experience the actual disappointment of basis risk.[18] Revenues from this round were the sum of realized yield multiplied by the price per bag of maize and potential payouts from insurance (for farmers who bought insurance and suffered losses but who did not incur basis risk) minus production and possibly insurance costs. After playing the three rounds, one round was randomly selected for making the actual payout.

5*.2.3. Dependent variables: knowledge and insurance demand*

We have two types of dependent variables. First, we asked farmers from both the control and treatment groups to participate in a knowledge quiz. We asked 15 knowledge questions about index insurance and basis risk, and our main knowledge variable is unweighted composite score of these 15 questions, normalized using the mean of the control group (see Appendix 5.4). We also explore whether the individual questions contribute equally to the overall knowledge score. We use a random forest machine learning algorithm to identify the knowledge questions that mattered

[17] The reason to not disclose the exact number of blue beads, even though farmers have an expectation of the number of blue beads, is to maintain a degree of ambiguity with regards to the true probability of basis risk, which is by definition ambiguous (if it could be precisely measured, it could be captured by an improved insurance product).
[18] For us, what matters most is that they had to take basis risk into consideration in their valuation of the insurance uptake decision.

most (see details in the appendix Section B3). Results from the random forest are corroborated with those from other algorithms, namely least absolute shrinkage and selection operator (lasso), decision tree, and k-nearest neighbors[19]. The main questions cover whether a farmer always receives a payout when they purchase insurance (sure payout), basis risk (basis risk knowledge), and the assessment of losses (loss assessment). In what follows we will also explore whether responses to these specific questions are affected by the interventions.

In addition to the effect of our interventions on "learning" (or knowledge), we are also interested in the impact on "demand for crop insurance". To measure this in an incentive-compatible manner, we offered all farmers to choose between a 200-shilling insurance discount voucher (for insurance in the approaching maize season) or an immediate cash offer. We presented each farmer with three choices involving three cash offers (Ksh.50, Ksh.100, Ksh.150), of which one choice would be effectuated (randomly determined).[20] The discount voucher covers the minimum allowed sum of insurance coverage, but can also be used to obtain a 200-shilling discount on the premium for a larger sum insured. Considering a weather index insurance that covers production costs and charges a premium of 10%, the 200 shillings voucher buys insurance worth Ksh. 2000, which is about the cost of improved seeds to plant an acre piece of land (Kirimi et al., 2018). The voucher could be redeemed through local agents of a known insurance company.

5.2.4. Data, household survey summary and balance

Data collected during the household survey include socio-demographic controls and farming variables: age of the farmer, household size, amount of inorganic fertilizer used per acre

[19] Results from all the algorithms show that knowledge about whether the farmer always receives a payout after purchasing insurance, knowledge about basis risk, and how losses are assessed caused the greatest variation in the knowledge about crop insurance.

[20] These values were determined in a pilot; not too low or too high. 1 USD dollar was equivalent to 110 Kenyan Shillings at the time of the experiment.

in kilograms, number of years of farming (experience), education, number of pieces of land owned by the farmer, fertilizer use, type of fertilizer used, experience with insurance (including health, car, and motor bicycle), main occupation, source of seeds, and maize farm size. We also collected data on behavioral factors that we suspected to correlate with demand for crop insurance, namely optimism bias (Sharot, 2011), prudence (Deck & Schesinger, 2014; Trautmann & Kuilen, 2018), risk aversion (Shin et al., 2022) and locus of control (Lefcourt, 1991).[21] We use the least absolute shrinkage and selection operator (LASSO) to select the most relevant controls to explain variation in our dependent variables (knowledge and demand for insurance), but obtain very similar results when applying a double-post-selection LASSO (not shown).[22] Table 5.1 summarizes the variables that "survived" the LASSO for both the knowledge and demand for insurance outcomes.

There are a few differences across experimental arms. For example, we find differences in whether the farmer had a college education (p=0.029) and used fertilizer (p=0.052). But the differences are small in number and magnitude. In some models we estimate below we control for the relevant covariates (those retained after the LASSO). We also did a joint orthogonality test to see if treatment correlated with the covariates. We fail to reject the null hypothesis that covariates and treatment are independent: p=0.125 for the model explaining variation in knowledge and p=0.257 for the model explaining variation in demand for insurance.

5.3. Empirical strategy and model specification

We examine the effect of our treatments on knowledge levels by estimating the following model:

$$K_i = \alpha + \beta_1 Narrative_i + \beta_2 Game_i + \beta_3 X_i + \beta_4 B_i + \epsilon_{1i} \quad \text{(E.5.1)}$$

[21] See Appendix Table 5.6 for more details for a description of the selected control variables.
[22] Cilliers et al. (2024) argues that the two approaches typically produce rather similar coefficients, but that the double-LASSO is more appropriate if attrition is high and covariates are correlated with the treatment. Both are not true for our experiment. Out of 1409 farmers participating in the survey, 1331 farmers also participated in the experiment, for an attrition rate of 6%. Attrition was independent of treatment (see Appendix 5.7).

where K_i is the knowledge score for farmer *i*, *Narrative* and *Game* capture assignment to the two treatment groups, and X_i and B_i capture demographic and behavioral factors, respectively, that survived the LASSO procedure. Coefficients β_1 and β_2 represent the average effects of the narrative information treatment and the game treatment on knowledge. We test the null hypotheses $\beta_1 = 0$ and $\beta_2 = 0$, and also the hypothesis $\beta_1 = \beta_2$. We then do a robustness analysis by re-estimating equation (E.5.1) but now replace the normalized knowledge score by each of the main questions contributing to knowledge as the dependent variables. This enables ascertaining whether the treatments influenced how farmers answered these questions.

Table 5.1: Description and balance of variables selected for regression analysis

	Overall	Control	Game	Narrative	P
	1331	331	667	333	value
Continuous variables					
Experience with insurance	2.09 (1.94)	2.03 (1.89)	2.09 (1.96)	2.16 (1.96)	0.278
Pieces of land owned	2.09 (1.35)	2.07 (1.27)	2.13 (1.39)	2.05 (1.35)	0.985
Household size	5.15 (2.45)	5.16 (2.25)	5.24 (2.54)	4.97 (2.43)	0.278
Categorical variables					
Male	602 (45.2)	144 (43.5)	292 (43.8)	166 (49.8)	**0.034**
Wanted insurance for next season	538 (40.4)	127 (38.4)	275 (41.2)	136 (40.8)	0.635
Wanted insurance immediately	210 (15.8)	52 (15.7)	105 (15.7)	53 (15.9)	0.978
Used seed from previous harvest	237 (17.8)	48 (14.5)	136 (20.4)	53 (15.9)	0.995
University education	31 (2.3)	9 (2.7)	16 (2.4)	6 (1.8)	0.287
College education	93 (7.0)	14 (4.2)	50 (7.5)	29 (8.7)	**0.029**
Secondary education	352 (26.4)	87 (26.3)	179 (26.8)	86 (25.8)	0.741
Age 46 - 55	320 (24.0)	74 (22.4)	162 (24.3)	84 (25.2)	0.238
Farming and other occupations	7 (0.5)	0 (0.0)	3 (0.4)	4 (1.2)	**0.038**
Farmer uses fertilizer	1072 (80.5)	272 (82.2)	517 (77.5)	283 (85.0)	**0.052**
Interest in insurance at baseline	1239 (93.1)	313 (94.6)	626 (93.9)	300 (90.1)	**0.048**
Not sure when to take insurance	277 (20.8)	75 (22.7)	148 (22.2)	54 (16.2)	0.107
Wanted insurance immediately	210 (15.8)	52 (15.7)	105 (15.7)	53 (15.9)	0.978
Access to weather information	833 (62.6)	200 (60.4)	412 (61.8)	221 (66.4)	0.106
Purchases seed	1069 (80.3)	275 (83.1)	519 (77.8)	275 (82.6)	0.717
Age 26 - 35	177 (13.3)	35 (10.6)	99 (14.8)	43 (12.9)	0.611
Technical education	62 (4.7)	19 (5.7)	26 (3.9)	17 (5.1)	0.730
Farmer uses organic fertilizer	182 (13.7)	39 (11.8)	96 (14.4)	47 (14.1)	0.603
Farmer uses inorganic fertilizer	516 (38.8)	134 (40.5)	252 (37.8)	130 (39.0)	0.815

Note: Values are in means for continuous variables and standard deviations in parentheses, and frequencies and percentages in parentheses for categorical variables. P-values were estimated using xbalance function in the R language. The function calculates standardized differences for stratified comparisons.

Next, we explore the effect of the two treatments on demand for insurance, for which we use an interval regression as in equation (E.5.2).

$$Y_i = \alpha + \sigma_1 Narrative_i + \sigma_2 Game_i + \sigma_3 X_i + \sigma_4 B_i + \epsilon_{2i} \quad \text{(E.5.2)}$$

where Y_i is the price interval at which the participant preferred cash over the insurance discount,[23] and the other variables are as before. We test the null hypotheses $\sigma_1 = 0$ and $\sigma_2 = 0$, and also the hypothesis $\sigma_1 = \sigma_2$.

Finally, we aim to improve our understanding of the mechanism that drives changes in demand for insurance by undertaking causal mediation analysis (Celli, 2022). Causal mechanisms analysis breaks the total treatment effect into two components, direct and indirect. The indirect effect is through an intermediate, endogenous variable, known as the mediator, which stands in-between the causal pathway of the intervention and the outcome variables (Imai et al., 2011). Denote Y_i as our outcome variable (the price interval), T_i as the treatment dummy for farmer *i,* and $M_i(t)$ as the potential value of a mediator variable *M* under treatment status *t*. Following Imai et al. (2011) the total treatment effect is given by:.

$$\tau_i = Y_i\big(1, M_i(1)\big) - Y_i\big(0, M_i(0)\big) \quad \text{(E.5.3)}$$

The indirect effect for individual *i* is defined in equation (E.5.4), the average direct effect (ADE) in equation (E.5.5), and the total effect is given by (E.5.6). We are interested in δ_i, the average causal mediation effect (ACME).

$$\delta_i(t) = Y_i\big(t, M_i(1)\big) - Y_i\big(t, M_i(0)\big) \quad \text{(E.5.4)}$$

$$\varphi_i(t) = Y_i\big(1, M_i(t)\big) - Y_i\big(0, M_i(t)\big) \quad \text{(E.5.5)}$$

$$\tau_i = \delta_i + \varphi_i(1 - t) \quad \text{(E.5.6)}$$

[23] We had four groups namely, 0-50, 50-100, 100-150, 150-200. 0 and 200 are lower and upper bounds that we introduce for the interval regression. We also transformed the cash offers into their natural logs.

We conduct the mediation analysis with one mechanism in mind, namely increased knowledge, and also control for farmers' experiences with basis risk in the game for the subsample of farmers in the Game treatment. We use the approach suggested by Imai et al. (2011). Since our mediator is a post-treatment variable, the requirement is that both the treatment and the mediator be "ignorable"—this is known as the sequential ignorability assumption. This assumption, represented by equations (E.5.7) and (E.5.8), implies that the treatment is independent of pre-treatment variables, and that there are no unmeasured pretreatment and posttreatment covariates confounding the relationship between knowledge (the mediator) and demand for insurance (the outcome), and that these covariates are not affected by the treatment (Imai et al., 2011):

$$\{Y_i(t', m), M_i t\} \perp\!\!\!\perp T_i | X_i = x \tag{E.5.7}$$

$$\{Y_i(t', m) \perp\!\!\!\perp M_i(t) | T_i = t, X_i = x \tag{E.5.8}$$

The first assumption is attained through randomization, but this is not necessarily true for the second criteria. To test whether this assumption is violated we follow two steps in the mediation analysis: (i) we estimate equation (1), the mediator equation, and (ii) we estimate equations (E.5.9) and (E.5.10). In (E.5.10) we separate in the game treatment the two sub-treatments with exogenously greater likelihood of being exposed to basis risk (*Basis*). All other variables are as in (E.5.2).

$$Y_i = \alpha_c + \varphi_1 Narrative_i + \varphi_2 Game_i + \varphi_3 K_i + \varphi_4 X_i + \varphi_5 B_i + \epsilon_{2i} \tag{E.5.9}$$

$$Y_i = \alpha_c + \varphi_1 Narrative_i + \varphi_2 Game_i + \varphi_3 K_i + \varphi_4 Basis10_i + \varphi_5 Basis15_i + \varphi_6 X_i + \varphi_7 B_i + \epsilon_{3i} \tag{E.5.10}$$

The sequential ignorability assumption cannot be ascertained directly, but Imai et al. (2011) suggest a sensitivity analysis based on assessing the correlation (ρ) between ϵ_{1i} and ϵ_{2i}.

Correlation between the error terms occurs when there are omitted variables in the two equations (Imai et al., 2010)[24]. Under the sequential ignorability assumption $\rho = 0$, and the size of ρ shows the extent to which the assumption is violated.

5.4. Results

We now present the empirical results. We ask first whether playing the game increased knowledge about crop insurance. Second, we examine whether game and narrative extension influenced demand for insurance. We then turn to the mediation analysis, which explores whether (how) knowledge and exposure to basis risk influenced demand for insurance.

5.4.1. Effect on knowledge

Table 5.2 shows results how the two extension modalities affect farmer knowledge. Models (1) and (2) are OLS regressions and models (3) to (5) present the marginal effects from probit regressions. In model (1) we only include treatment dummies as covariates and model (2) includes control variables selected through LASSO. Models (3), (4), and (5) are regressions with the three "main distinguishing questions" as dependent variables, as determined by the machine learning random forest algorithm. The results show that playing the game and receiving narrative information both significantly increased farmers' knowledge about crop insurance, compared to the control group. The Game modality outperforms the Narrative modality,[25] and the difference between coefficients of the game and narrative treatments (0.14 SD) is statistically significant different from zero (p=0.012).

[24] The reliability of the use of error correlations has been questioned (Imai et al., 2010). However, all the other alternative approaches suffer from similar challenges (Qin & Yang, 2021).

[25] The effect of the interventions on knowledge may not be homogeneous across the study group. We provide details on this ex-post (exploratory) analysis in the appendix (see Appendix 5.13 for details on heterogeneous treatment effects).

Table 5.2: Effect of the game and receiving information on knowledge

	(1)	(2)	(3)	(4)	(5)
	Overall		Payout uncertainty	Basis risk	Loss verification
Game	0.994***	0.974***	0.652***	1.690***	1.401***
	(0.059)	(0.055)	(0.092)	(0.106)	(0.112)
Narrative	0.877***	0.840***	0.481***	1.303***	1.267***
	(0.065)	(0.062)	(0.105)	(0.115)	(0.124)
Mean of control	8.338	8.338			
Additional controls	No	Yes	Yes	Yes	Yes
Game = Narrative F-test p-value	0.038	0.012	0.059	0.000	0.149
Number of observations	1331	1331	1331	1331	1331
Adjusted R2	0.329	0.416			
AIC	3177.3	3003.0	1634.1	1362.7	1413.3
Log likelihood			−788.072	−652.326	−677.642

Notes: Control variables are experience with insurance, pieces of land owned, university education, college education, secondary education, farmer uses fertilizer, age 46–55, purchased seeds, farming plus other occupations, organic fertilizer, and seed from previous harvest, and wanted insurance in the next season. The standard errors are robust, clustered at sub-location level. The F-test p value shows whether the game and narrative coefficients are statistically different. Results are robust when we (do not) control for unbalanced covariates (see details in section C4 of the appendix). Significance: *** = $p < 0.01$; ** = $p < 0.05$; * = $p < 0.1$.

Results from models (3), (4), and (5) show that farmers in *Game* and *Narrative* had a higher likelihood of answering the three main questions correctly, compared to farmers from the control group. The difference in coefficients of the Game and Narrative variables is statistically significant at 1% for the basis risk knowledge question (model 4) and at 10% for the question on certainty in payouts, but not for the question on loss verification. We also observe a difference in the percentage of farmers correctly answering the question about basis risk. Only 21% of the farmers in the control

group answered this question correctly, compared to 75% and 65% of farmers in the game and narrative groups (see details in Appendix Table 4.3).

These findings corroborate findings from Janzen et al. (2021) and Cai & Song (2017), who also find that these extension modalities "work". Compared to Janzen et al. (2021), our "horse race" design enables comparing the incremental effect of the game by itself, as well as the effect of each treatment relative to the pure control. Our findings that *Game* does better in enhancing knowledge accumulation stands in contrast with findings from (Patt et al., 2010) and Tessema et al. (2021) who found no difference in performance between games and conventional training. Perhaps this difference is because our subjects (and those in Janzen et al. 2021) played an incentivized game, as opposed to the non-incentivized games in these two studies.

5.4.2. Effect on demand

Figure 5.2 shows the percentage of farmers preferring the insurance discount over the cash offers. Not surprisingly, preference for the insurance discount decreases as the cash offer increases—this simply captures downward sloping demand for the insurance product. More interesting is that the percentage of farmers preferring the cash offer is consistently higher for experiential learning participants than for the other two groups, across all cash offers. This suggests the demand curve for insurance has shifted inward. The shift in the demand curve might reflect a shift in preferences—experiencing shocks may make farmers more tolerant to risk in some domains (Finger et al., 2023)[26] We scrutinize further whether (and why) playing the game and receiving information about insurance causes this shift in demand for crop insurance. Table 5.3

[26] Halevy (2015) also shows that individuals' preferences are time-variant even after controlling for implicit risk and demand for liquidity.

summarizes the regression results of model explaining variation in demand for insurance[27]. Model (1) includes treatment dummies only, while model (2) includes control variables.

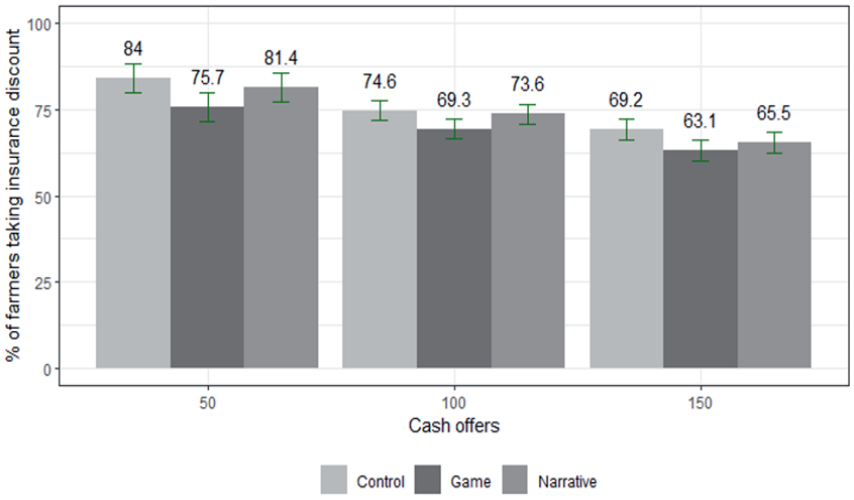


Figure 5.2: Proportion of farmers preferring cash to insurance discount

The regression results show that playing the insurance game had a small but significant negative effect on demand for insurance. In particular, playing the game reduces the probability that farmers choose the insurance discount by about 10 percentage points.

Table 5.3: Effect of playing the game and receiving information on demand for insurance

	(1)	(2)
Game	−0.111***	−0.102***
	(0.039)	(0.037)
Narrative	−0.026	−0.014
	(0.043)	(0.044)
Mean of the control	0.76	0.76
Additional controls	No	Yes
Game = *Narrative*, F-test *p*-value	0.038	0.038

[27] The results are relatively the same when we use an alternative specification and are not sensitive to whether we cluster standard errors at the sublocation level or not (see more details in the appendix—Table 5).

	(1)	(2)
Number of observations	1331	1331
AIC	4970.6	4957.3

Notes: Control variables include household size, amount of organic fertilizer, gender (male), age 26 – 35, university education, farmer uses organic fertilizer, purchases seed, access to weather information, farmers irrigates maize, and interest in insurance at baseline. The standard errors are robust, clustered at sub-location level. We also control for enumerator effects. The mean of the control is the average percentage of farmers who preferred the insurance voucher across the cash offers. The F test p-values show whether the game coefficient is the same as the narrative coefficient. Results are robust when we (do not) control for unbalanced covariates (see details in section C4 of the appendix). Significance: *** = $p < 0.01$; ** = $p < 0.05$; * = $p < 0.1$.

5.4.3. Mediation analysis

Why did participating in the game have a negative effect on demand? To answer this question, we assess whether this effect is caused by a change in knowledge or whether additional factors play a role. The literature says that the role of knowledge in technology adoption is inconclusive––some studies find knowledge is an important determinant (e.g. Van Campenhout et al., 2021) and others do not (for example De Brauw et al., 2018; Hörner et al., 2022). The literature on index insurance adoption found that basis risk is an important barrier to adoption (Kramer et al., 2022). We explore whether "experiencing" basis risk in the game is a salient experience and has an independent effect on demand—over and above the effect of understanding what basis risk is (as captured by the knowledge mediator). Our experimental design implies that we have exogenous variation in exposure to basis risk.

The estimation results of (9) and (10) are in Table 5.4. We assume a linear demand function for insurance and treat knowledge as a mediator. In column (1) we probe the correlation between knowledge and demand, and in column (2) we add treatment dummies to test if the treatment affects the outcome after controlling for the knowledge mediator. In column (3) we introduce dummies for participating in a game treatment with "high basis risk" (10% or 15%). In column (4)

we interact knowledge with the highest degree of basis risk to test if greater knowledge had a differential effect when exposed to greater likelihoods of basis risk (to check for a violation of the sequential ignorability assumption).

Across all models we find a negative association between knowledge and the probability of choosing the insurance voucher. This result is consistent with a story where, on average, farmers tend to be optimistic about the value of index insurance and learning about how index insurance actually works reduces the attractiveness of the insurance product. This is true for narrative-based learning and experiential learning. A one standard deviation increase in the knowledge score reduces insurance uptake by 5 percentage points. Since experiential learning is more effective than narrative-based learning, on average the demand-reducing effect of knowledge is greater for subjects in the Game treatment. Including both the knowledge variable and treatment dummies shows how knowledge mediates the treatment effects (column 2). The *Game* dummy is not statistically different from zero, and the coefficient is much smaller than before.

Table 5.4: Mechanisms analysis, extension modalities and demand for insurance

	(1)	(2)	(3)	(4)
Knowledge	−0.042**	−0.046**	−0.048**	−0.053**
	(0.018)	(0.021)	(0.022)	(0.023)
Game		−0.057	0.013	0.019
		(0.043)	(0.062)	(0.064)
Narrative		0.008	0.009	0.014
		(0.052)	(0.052)	(0.052)
10% basis risk			−0.069	−0.069
			(0.067)	(0.067)
15% basis risk			−0.134**	−0.161**
			(0.060)	(0.077)
Knowledge × 15% basis risk				0.031
				(0.048)

	(1)	(2)	(3)	(4)
Mean of the control	0.76	0.76	0.76	0.76
Additional controls	Yes	Yes	Yes	Yes
Number of observations	1331	1331	1331	1331
AIC	5073.2	5059.3	5058.5	5060.2

Notes: Control variables include household size, interest in insurance at baseline, use of organic fertilizer, amount of organic fertilizer, gender (male), age 26 – 35, education, purchases seed, access to weather information, wanted insurance immediately, farmer was not sure when they would need insurance. The standard errors are robust, clustered at sub-location level. The mean of the control is the average percentage of farmers who preferred the insurance voucher across the cash offers. Significance: *** = $p < 0.01$; ** = $p < 0.05$; * = $p < 0.1$.

But this is not all. If we introduce dummies to capture exposure to basis risk, we find that exposure to a high level of basis risk (15%) reduces demand for insurance (column 3).[28] The knowledge variable remains a significant determinant of demand, and its magnitude is hardly affected by the basis risk dummy. The demand-reducing effect of basis risk therefore appears to be over-and above the mediating effect of knowledge. Narrative-based learning and experiential learning both cause subjects to learn about basis risk and understand what it does (as is evident from the test questions), *but this is not the same as experiencing high basis risk firsthand*. This goes back to the premise of Experiential Learning Theory (ELT), discussed in the introduction. Since farmers in *Game* have more knowledge than farmers in *Narrative*, on average, they are willing to pay less for the insurance product. Farmers in *Game* who were exposed to high basis risk further reduced their willingness to pay. Games enable subjects to learn, and generate "experiences" unique only to players (Landers et al., 2019), which have an independent effect on preference formation.[29] In column (4) we interact knowledge and exposure to high basis risk. This

[28] This negative effect is in line with earlier studies (e.g., Elabed & Carter, 2015; Hill et al., 2013; Janzen et al., 2021; Serfilippi & Ramnath, 2018), and is consistent with a rational valuation of the insurance (since in our experiment basis risk is only negative, it lowers the actuarial value of the insurance).

[29] Game elements such as badges, levels, leaderboards, and rewards like in our case motivate (intrinsic or extrinsic) the learner, factors that make games effective (Sailer et al., 2017).

interaction term is not significant, corroborating the validity of our mediation analysis with respect to knowledge (Imai et al., 2011).

Next, we calculate ACME and Average Direct Effect (ADE), and report results in Table 5.5. Without controlling for basis risk (Panel A), both the ACME, ADE and proportion mediated by knowledge are significant. The ACME explains about 44% of the total effect of knowledge on demand for insurance at 5% significance level.[30] The mediating role of knowledge on demand for insurance persists after controlling for basis risk (Panel B). The ACME is significant at 5% and explains 53% of the total effect.

Table 5.5: ACME and ADE from the mediation analysis

	Estimate	95% CI Lower	95% CI Upper	*p*-value
Panel A: Without basis risk				
ACME	-0.043	-0.08	-0.004	**0.028**
ADE	-0.058	-0.142	0.021	0.172
Total Effect	-0.100	-0.178	-0.029	**0.004**
Proportion Mediated	0.437	0.044	1.562	**0.032**
Panel B: With basis risk				
ACME	-0.044	-0.082	-0.006	**0.032**
ADE	0.014	-0.102	0.133	0.780
Total Effect	-0.030	-0.133	0.079	0.570
Proportion Mediated	0.530	-10.823	8.495	0.582

Note: CI is the confidence interval, ACME is the average causal mediation effect, ADE is the average direct effect, while proportion mediated is the percentage of the ACME as a fraction of the total effect.

[30] De Brauw et al. (2018) find a similar effect on the adoption of orange fleshed sweet potato among farmers in Uganda but find no causal mediation effect for farmers in Mozambique.

Next, we conduct a sensitivity analysis as suggested by Imai et al. (2010) to test whether the causal mediation effects are robust to the sequential ignorability assumption. As mentioned earlier, this analysis assesses whether there are omitted confounders between the outcome and mediator equations by considering the correlation (ρ) between the error terms of two equations. We estimate ACME over the whole range of ρ (-1 to 1), which has both conceptual and practical limitations (Keele et al., 2015). There is no accepted threshold to judge whether a result is "unacceptable", and the analysis supports only a limited number of mediator-outcome model combinations. For this reason, we do not use our preferred models (see Appendix 5.12), so the results we present are "conservative". We visualize the findings from the sensitivity analysis in Figure 3 (panel B is a zoomed in version of A). The results show that ACME is less than -0.1 when $\rho = 0$, implying that our results are sensitive to small changes in ρ.

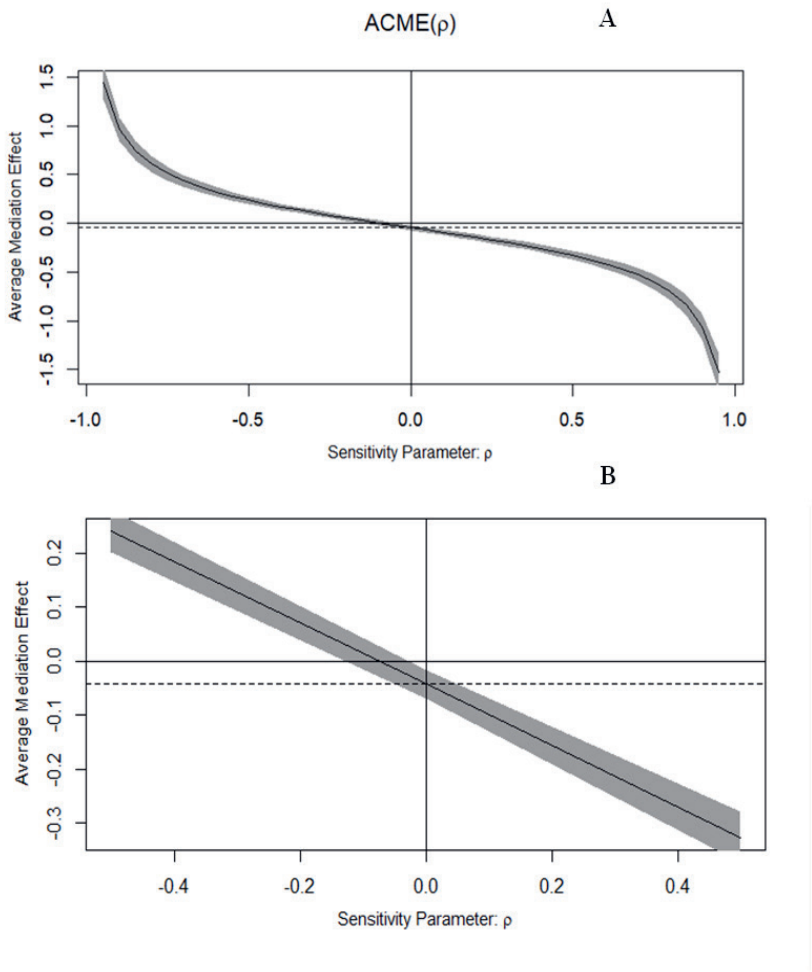


Figure 5.3: ACME as a function of ρ.

Notes: The broken line represents the ACME when ρ is zero, the grey regions show the 95% confidence interval for ACME at different values of ρ, and the solid line is the ACME at each value of ρ.

5.5. Discussion and conclusions

Lack of information is an important explanation for imperfect technology adoption by small scale farmers (Takahashi et al., 2020). One strategy suggested in the literature to promote the adoption of innovations is to increase the effectiveness of informational interventions (Bridle et al., 2020; Suri & Udry, 2022). This can be achieved through pioneering alternative approaches

in delivering information to farmers—other than the conventional descriptive extension modality (Kaiser & Menkhoff, 2022). Game-based learning is one such approach. Though games have been used a few times to educate farmers, there is a paucity of evidence on their effectiveness vis-à-vis conventional training approaches. This ambiguity concerns both the impact of experiential learning on knowledge levels and subsequent behavior, including technology adoption.

We use a framed field experiment with an incentive compatible game component in one of the treatments to test whether: (i) games are superior in enhancing knowledge compared to conventional narrative-based approaches, (ii) information transfer affects demand for index insurance, and (iii) experiences during the game affect demand for insurance after the experiment. We find that the framed insurance experiment we designed is superior to narrative information in enhancing knowledge. Compared to the control group, both approaches increase knowledge by approximately one standard deviation, so both approaches help farmers to understand complex concepts such as crop insurance and basis risk. However, experiential learning outperformed the narrative-based approach: playing the insurance game not only helps to accumulate knowledge but also generates experiences that deepen the learning process and raise awareness of possible non-performance of the insurance product.

Unlike narrative-based learning, we find that game-based learning significantly influenced demand for insurance – and the net effect was negative. Higher knowledge levels are associated with reduced demand, and experiences with high basis risk during the game push down demand further. In theory, the impact of experiential learning on adoption is ambiguous, depending on prior understanding of the product and expectations with respect to its performance. In our case, the net effect was negative as farmers better understood and operationalized the concepts of basis risk and its adverse consequences than before the game. Our results underscore the need of addressing basis

risk in index-based insurance products and the need to design products that cover the most important risks of the farmer to increase the relevance of the products for farmers seeking to manage their production risks.

Our paper is close to Janzen et al. (2021), who also study experiential learning and demand for insurance. They find that conditional on being offered high basis risk insurance, playing their game increased demand, whereas playing their game had no effect on demand conditional on being offered low basis risk insurance. Conditional on not playing the game, being offered low basis risk insurance increased demand. The authors refer to this counter-intuitive result as "surprising" and rationalize it by arguing that the low basis risk product may have performed worse than expected by the farmers and the high basis risk product may have performed better than expected.[31] An important difference between that study and ours is that farmers playing the game in Janzen et al. (2021) first participated in a narrative-based learning session, and therefore were "primed" to form expectations about the insurance product and exposure to basis risk. In contrast, farmers in our game did not receive narrative-based extension and, hence, were not challenged to form such expectations prior to playing. They simply experienced low or high basis risk during the game and proved able to differentiate their valuation based on their level of exposure. Sensitivity to exposure to basis risk was evident during the follow-up demand revelation exercise. Another difference between Janzen et al. (2021) and this paper is that their valuation exercise is based on stated preference while we use an incentive-compatible approach to measure preferences for actual products after the game.

Learning about the advantages and disadvantages of insurance products, like other agricultural technologies, can take a lot of time in "reality" (Maertens et al., 2021). The results of

[31] They develop a model with reference-dependent learning and loss aversion, resulting in misattribution bias.

this paper extend well beyond the domain of insurance. In fact, while the sign of the effects observed in our study may be unique to some characteristics of index insurance, the mechanism through which we observe changes in demand applies to the adoption of any innovations in farm production. Learning through on-farm experimentation may involve (opportunity) costs and could be misleading depending on the sequence of signals that farmers receive about performance (varying with the weather etc.). Incorporating carefully designed experiential learning elements has the potential to reduce the cost associated with experimentation, and can generate "real life" experiences in a shorter time (e.g., Tjernström et al., 2021). Insights from how farmers behave in games can subsequently be used to improve innovations, focusing on those features that matter most to farmers. Of course there are also costs, especially in the short run, associated with using games as extension tools. The implementation of game-based learning requires additional training of extension officers, so governments and donors could consider allocating additional resources to employing and training extension agents. Alternatively, an enabling environment could be created within which the private sector provides such extension services (Dar et al., 2024).

Our study is not without limitations. Our approach to game-based or experiential learning, particularly concerning knowledge accumulation, is relatively broad. We rely on an extrinsic incentive mechanism—an incentive provided outside the game itself. However, intrinsic incentive mechanisms, embedded directly within the game, such as points, badges, leaderboards, and levels, may impact both knowledge accumulation and player motivation differently. Further exploration of these embedded incentives and their effects is needed to fully understand the rubrics of game-based/experiential learning. Additionally, we do not examine whether experiential learning creates a lasting knowledge effect (and for how long) compared to a narrative-based intervention. Evidence shows that knowledge (experience) from information interventions fades with time (e.g.,

Hoffmann et al., 2021). Assessing knowledge over a longer period would offer additional insights into the cost-effectiveness of game-based learning as an alternative extension tool.

Appendix 5

Appendix 5.1: Crop insurance game protocol

Appendix Table 5.1: Game protocol

STEP	Points to cover
INTRO OF THE GAME	1. The game we play first is about risks in maize production and insurance products as a potential market-based risk management mechanism. 2. We will play the game for three rounds. 3. In each of the three rounds of play, the enumerator should note the amount of money the farmer should receive (compensated) based on the following descriptions. 4. In the first stage of round one, we will offer you 12,000 game currency shillings (100 game currency is equivalent to Ksh. 1) that you will use to produce maize in the game context. The cost of production for a season is 10,000 shillings of game currency. 5. After this explanation, ask the farmer how much she would remain with after producing maize to ensure that she understands. Proceed to the next steps if and only if the farmer gives the right answer (2,000 shillings), otherwise repeat the explanation, until the farmer understands. 6. In the game context, you will face two main risks when you produce maize namely drought/dry spell and pests and diseases. Whether you experience yield losses from these risks will depend on the choices you make in the next steps of the game, and chance as we explain in a short while. 7. In the game context, you may get a maximum of 20 bags of maize per acre if the season is good (meaning that there is no drought and there are no losses from pests and diseases), or a minimum of 4 bags of maize per acre if the season is bad, meaning that you suffer losses from one, or both risks. In the game currency, each bag of maize sells for 2,500 shillings. 8. At this point, ask the farmer how much she would gain if she chose to produce maize, and the season turned out to be good (bad). Earnings from a good season should be Ksh. 52,000 (equivalent to Ksh. 520), while earnings in the

	bad season should be 12,000 shillings (equivalent to Ksh. 120). Continue with the next steps if and only if the farmer affirms that she understands, otherwise repeat the explanation, until she understands. 9. In round two, we will also produce maize but in this case, we will offer you crop insurance to cover you from any yield losses arising from the risks, however you must pay for the insurance at the beginning of the season using some of the game money we offer you. 10. In the third round, we will still offer you insurance with a slight difference from round two (basis risk) as we will explain when we play the round. 11. At this point emphasize to the farmer that it is important to play all the three rounds since we will have a better understanding of her preferences. The farmer will also be learning better on how insurance works through playing all the three rounds. 12. Lastly, you will randomly select a round that will be compensated with real money. Remember that: a. Round 1 has no crop insurance. b. Round 2 has insurance that compensates any yield losses arising from unreliable rainfall and pests and diseases. c. Round 3 has insurance, but compensation depends on chance (probability). d. The maximum earning you can get is Ksh. 520 while the minimum is Ksh. 120.
Insurance and production game	
ROUND 1	1. We will play this first round of the game without insurance. However, before we start, I will ask you a question that will help you understand the game better. 2. On a normal year (usually) when the rainfall is reliable and there are no outbreaks of pests and diseases, how many bags of maize do you harvest from one acre of land? Enumerator to record the number of bags the farmer mentions.

	3. For the sake of our game today, the normal yield will be 12 bags per acre. However, if there is a drought, the minimum yield you will get will be 4 bags per acre, while the maximum yield if rainfall is reliable and there are outbreaks of pests and diseases is 20 bags per acre. 4. We will offer you 12,000 shillings of game currency which will finance your production activities. Your cost of production is 10,000 shillings of game currency. 5. At this point, hand the farmer the fake money amounting to 12,000 shillings. 6. Now, let us go through the steps of producing maize. 7. There are two sets of bags, bag A and bag B. Bag A represents drought while bag B represents pests and diseases. 8. Each of the two pet jars contains 11 beads numbered 0, 0, 1, 1, 2, 4, 0, -1, -1, -2 and -4. The numbers correspond to yield losses associated with each risk. Remember that the yield losses are deficits (surpluses) from normal yield per acre of land which is 12 bags. 9. At this point, show the farmer the beads and the numbers written on them. The enumerator should ensure that s/he has all the beads. 10. Step 1: Select a bead from bag A (losses associated with drought). 11. Step 2: Select another bead from bag B (losses associated with pests and diseases). 12. Your final yield loss will be as shown in the table below, in that if you choose a bead labelled -4 from bag A and a bead labelled -2 from bag B then your yield loss will be 6 bags of maize. This means that your final yield from your production activities will be 6 bags of maize per acre (12 -6). If you choose a bead labelled 4 from bag A, and another labelled -1 from bag B, it means that your final yield will be 12 + 4-1, which is 15 bags per acre. If you choose zero from both bags, then it means you suffer no loss (below the normal yield) from the two risks (your yield will be 12 bags per acre).

Bag B

Bag A	-4	-2	-1	-1	0	0	0	1	1	2	4
-4	-8	-6	-5	-5	-4	-4	-4	-3	-3	-2	0
-2	-6	-4	-3	-3	-2	-2	-2	-1	-1	0	2
-1	-5	-3	-2	-2	-1	-1	-1	0	0	1	3
-1	-5	-3	-2	-2	-1	-1	-1	0	0	1	3
0	-4	-2	-1	-1	0	0	0	1	1	2	4
0	-4	-2	-1	-1	0	0	0	1	1	2	4
0	-4	-2	-1	-1	0	0	0	1	1	2	4
1	-3	-1	0	0	1	1	1	2	2	3	5
1	-3	-1	0	0	0	1	2	2	2	3	5
2	-2	0	1	1	2	2	2	3	3	4	6
4	0	2	3	3	4	4	4	5	5	6	8

13. At this point, play the game a few times with the farmer for practice. Play the game for "real" once the farmer properly understands. Let the farmer know when she is playing the final round that will be used as final data (yield).
14. Your final earning from this round is the product of your final yield and the price of a bag of maize (2,500 shillings of game currency).
15. At this point, ask the farmer what her revenue would be if she got 8 bags in the end. The farmer should mention 22,000 shillings for you to move to the next round. Otherwise, explain to her until she understands.
16. Enumerator should note the amount of money the farmer should be compensated.

Round 2 (there were variations based on the insurance cover of the farmer)

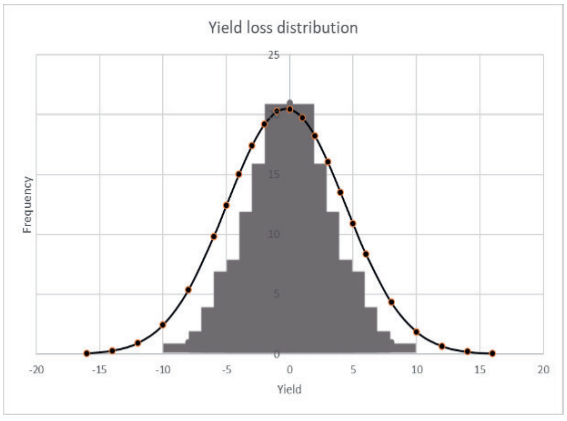
ROUND 2	17. We will play the game again as we did in round 1, but in this case with a crop insurance cover that completely covers losses from one risk. 18. The product covers losses arising from drought only even though you face both risks. 19. The insurance product will compensate you 500 game shillings for every bag of maize you lose. 20. At this point, the enumerator should ask the farmer how much money she would get compensated if she lost:

	a. 8 bags (farmer should say 4000 shillings, otherwise explain until she understands) b. 2 bags (farmer should say 800 shillings, otherwise explain until she understands) c. 5 bags (farmer should say 2500 shillings, otherwise explain until she understands) 21. We again give you 12,000 shillings of game currency to finance your production activities. Remember that your cost of production is 10,000 shillings and that, we offer you a crop cover that compensates 500 shillings for every bag of maize you lose due to drought. You must buy the insurance at the beginning of the season. You have 2,000 shillings, from which you can spend on the crop insurance. 22. Let us now determine the price at which you will buy the insurance cover. 23. Step 1: What is the maximum amount of money will you be willing to pay for such an insurance product (enumerator to remind the farmer about the product). Remember that the cost is per acre of land (price 1). 24. Step 2: Suppose the insurance cover was offered to you at a slightly higher price than your mentioned price (price 1), how much would you pay for it (price 2)? 25. Step 3: Suppose the insurance cover was offered to you at a slightly higher price than price 2, how much would you be willing to pay for the cover? 26. Repeat this procedure until the farmer is not willing to change the price. 27. Now we determine whether you will purchase the cover or not. 28. This bag (enumerator to show the third bag to the farmer) contains 3 pieces of paper with prices on them. I will ask you to draw one price (paper) from the bag. 29. If the price you draw is less than your maximum bidding, then you pay for the product at the price you drew from the bag. If the price you draw is more, then you do not buy the insurance product. Note: The enumerator should not reveal the prices to the farmer!

	30. Remember that your final revenue will be total revenue (number of bags multiplied by the price per bag) less production cost and the cost of insurance. 31. Once you have purchased (not purchased the insurance), we can now go ahead to produce maize again as we did in round one. The enumerator should take the farmer through the steps of yield determination as in round 1: a. Select a bead from bag A b. Again, select another bead from bag B c. Determine yield as in round 1 32. If you experience losses from drought (bag A), we compensate you 500 shillings at the end of the season, otherwise you do not get compensated. 33. Enumerator should enter the amount of money the farmer should be compensated.
***Round three**: 5 % basis risk sub-group (there were three levels of basis risk)*	
ROUND 3	9. We will play the game again as we did in round 2 with insurance. However, you will not always receive compensation when you incur a loss because of many reasons including poor verification of losses, wrong entry of data or any other technical issues. We call this basis risk. 10. In our game, you must pick a green bead from a fourth bag as we explain in the next steps for you to get compensated. 11. Follow steps 2 to 14 as in round 2. In summary: j. Remind the farmers that the insurance product compensates 500 shilling for every bag of maize lost because of drought. k. Determine the price at which the farmer will buy the insurance by: l. Asking the farmer her initial bidding price m. Ask again if the farmer is willing to buy the product at a slightly higher price n. Repeat procedure of asking price as in d above until the farmer is no longer willing to adjust her price o. After determining the insurance price, proceed to determine the yield p. Ask the farmer to select a bead from bag A q. Ask the farmer again to select another bead from bag B

	r. Determine the final yield as in round 1. 12. If you experience losses because of drought (jar A), we compensate you at the end of the season 500 shillings for every bag of maize lost. Remember that you will be compensated only if you select a green bead from this fourth bag. 13. The fourth bag contains 10 beads of which 9 to 10 are green. 14. Select a bead from the bag. 15. If you choose a green bead, then we compensate 500 shillings for every bag you lose, otherwise you do not get compensated. 16. Once you have selected a bead, I will reveal to you the number of green beads in the bag. 17. Enumerator should reveal the number of green beads to the farmer so that the farmer confirms that indeed there were green beads in the bag. 18. Enumerator must record the amount of money the farmer should be compensated.

Appendix 5.2. Yield distributions in the game



Appendix Figure 5.1: Yield loss distributions

Appendix 5.3. Narrative information script

Appendix Table 5.2: Narrative information treatment

Information on insurance (narrative group)	
INFO ON INSURANCE (narrative)	**What is insurance** It is a risk management strategy, where you get to transfer risk to another (person or entity) at a certain cost, that is lower compared to the loss you would otherwise incur. An example is health or car insurance. **Premium** A premium is the money you pay for the insurance. For example, the monthly contribution of the NHIF is the premium. The amount you pay for insurance depends on the insurance cover. Insurances that cover many perils are likely to be more expensive. For crop insurance, you usually pay a premium before the start of the season. **Crop insurance** This is insurance that covers farmers from yield losses caused by many factors. The most common insurance cover is against drought. However, there are insurance products that cover other factors such as input and output prices, pests and diseases, hailstorms in some countries, and fires among others. **Number of risks covered** Crop insurance can cover many risks. The most common insurance products for maize cover one risk. **Types of crop insurance** *Indemnity based:* Loss verification done on the farmer's field, or neighbors that is in the same region as the subject farmer's. *Index-based:* Losses are assessed without necessarily coming to the farm to measure the losses. The assessment can be done through satellite imagery. **Basis risk** You will not always receive compensation when you incur a loss because of many reasons including poor verification of losses, wrong entry of data or any

	other technical issues. Losses on the farm may not always be captured by the insurer. We call this basis risk. **Payouts from insurance example** Imagine you usually get 10 bags of maize per acre when the season is good. If the season is not good (there was drought and pests and diseases for instance), you might get less than 10 bags per acre. If you had subscribed to an insurance that completely covers one risk (drought) even though you might experience losses from pests and diseases, you will be compensated a certain amount of money for each bag lost because of drought. For example, if in a season you lose 4 bags of maize because of drought, and another 4 bags from pests and diseases, then the insurance will compensate you a certain amount of money (say 500 shillings) for each of the 4 bags of maize you lose because of drought. However, the insurer needs to verify the losses. Remember that if you lose 1 bag from drought, and 4 bags from pests and diseases, then the insurance will compensate only the loss from drought (1 bag).
TESTING (farmer understanding on payouts)	1. Imagine you bought an insurance that compensates if you experience losses from drought. Your normal yield is 12 bags per acre. 2. Also imagine a dry season, where because of drought, you get just 6 bags of maize. How many bags of maize will you be compensated by the insurance? 3. Enumerators should only move to the next step if the farmer gives the right answer. Otherwise, explain to the farmer until she understands.

Appendix 5.4: Questions testing learning effect of the insurance game (every question is 1 point)

1. When you have purchased crop insurance, you must always be compensated at the end of the season (True/**False**)
2. When you have purchased crop insurance, you do not need to take care of your crop (True/**False**)
3. There are crop insurance products existing that can cover more than one risk (**True**/False)
4. Insurance products can only cover drought (True/**False**)
5. What is the term used to refer to an instance where insurance fails to pay even when you suffer a loss?
    a. Loss
    b. Theft
    c. Basis risk
    d. I don't know
6. If you purchased crop insurance, the insurance always pays the whole amount of the loss you incur (True/**False**)
7. When you have purchased crop insurance, you still need to take care of your crop (**True**/False)
8. Insurers always come to the farm to assess losses for all farmers who purchase crop insurance in case of a claim (True/**False**).
9. If you purchase a rainfall insurance for maize, and in that season, there is a pest invasion (locusts) that results in you losing your whole crop, then the insurance should compensate you (True/**False**).
10. When you have purchased crop insurance, you are not always compensated at the end of the season (**True**/False)
11. Imagine you bought an insurance that compensates 500 shillings for every bag lost if you experience yield losses from drought. Your normal yield is 12 bags per acre. Also imagine a dry season, where because of drought, you just get only 6 bags of maize at the end of the season. How much will you be compensated by the insurance?
    a. 0
    b. 500

c. 3000

d. 10000

12. Insurance products can cover many other risks other than drought (**True**/False)
13. Imagine you bought an insurance that compensates 500 shillings for every bag of maize lost if you experience yield losses from drought. Your normal yield is 12 bags per acre. Also imagine a season where you get 6 bags of maize only because of an invasion by locusts. How much will you be compensated by the insurance?

    a. 0

    b. 500

    c. 3000

    d. 10000

14. Insurers will not always come to the farm to assess losses for all farmers who purchase crop insurance in case of a claim (**True**/False).
15. If you purchased crop insurance, the insurance will not always pay the whole amount of the losses you incur (**True**/False).

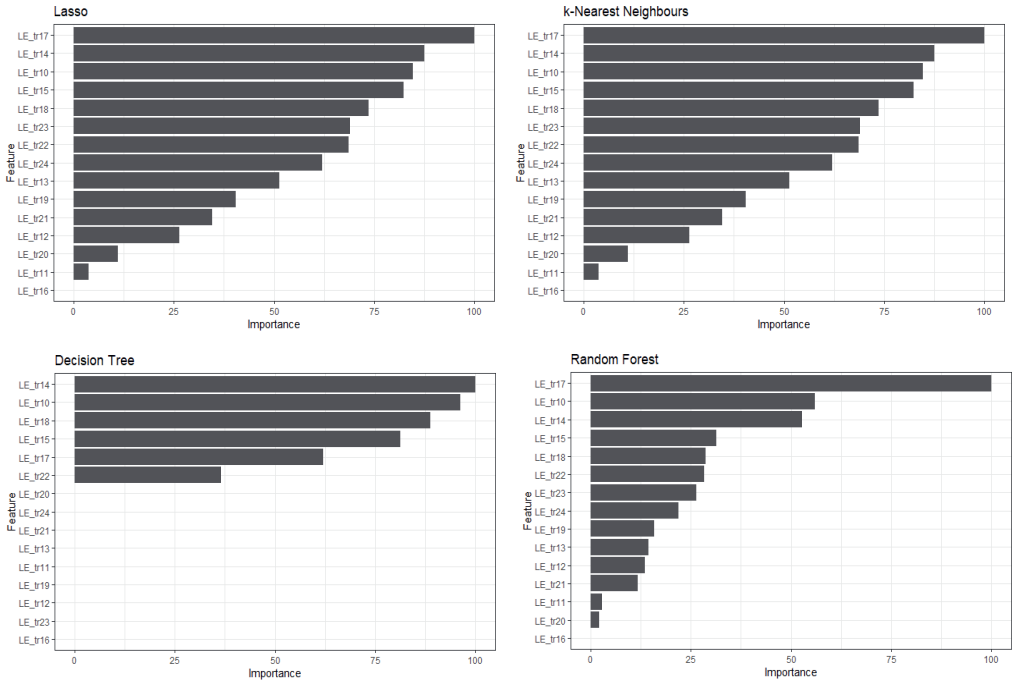
Appendix 5.5: Percentage of farmers answering questions correctly

Appendix Table 5.3: Percentages of farmers answering the questions correctly

Questions	Control (N=331)	Game (N=667)	Narrative N = 333
	Percentages		
When you have purchased crop insurance, you must always be compensated at the end of the season (True/**False**)	42	62	58
When you have purchased crop insurance, you do not need to take care of your crop (True/**False**)	95	93	96
There are crop insurance products existing that can cover more than one risk (**True**/False)	75	87	83
Insurance products can only cover drought (True/**False**)	53	67	64
What is the term used to refer to an instance where insurance fails to pay even when you suffer a loss? (1=Loss; 2=Theft; 3=**Basis risk**; 4= I don't know)	21	75	65
If you purchased crop insurance, the insurance always pays the whole amount of the loss you incur (True/**False**)	29	52	50
When you have purchased crop insurance, you still need to take care of your crop (**True**/False)	98	99	99
Insurers always come to the farm to assess losses for all farmers who purchase crop insurance in case of a claim (True/**False**).	14	52	47
If you purchase a rainfall insurance for maize, and in that season, there is a pest invasion (locusts) that results in you losing your whole crop, then the insurance should compensate you (True/**False**).	47	73	72
When you have purchased crop insurance, you are not always compensated at the end of the season (**True**/False)	62	64	67

Imagine you bought an insurance that compensates 500 shillings for every bag lost if you experience yield losses from drought. Your normal yield is 12 bags per acre. Also imagine a dry season, where because of drought, you get only 6 bags of maize at the end of the season. How much will you be compensated by the insurance? (1=0; 2=500; 3=**3000**; 4=10000)	93	96	97
Insurance products can cover many other risks other than drought (**True**/False)	83	86	84
Imagine you bought an insurance that compensates 500 shillings for every bag of maize lost if you experience yield losses from drought. Your normal yield is 12 bags per acre. Also imagine a season where you get 6 bags of maize only because of an invasion by locusts. How much will you be compensated by the insurance? (1=**0**; 2=500; 3=3000; 4=10000)	33	53	53
Insurers will not always come to the farm to assess losses for all farmers who purchase crop insurance in case of a claim (**True**/False).	41	69	70
If you purchased crop insurance, the insurance will not always pay the whole amount of the losses you incur (**True**/False).	48	70	65

Appendix 5.6: Output from machine learning analysis of the main questions



Appendix Figure 5.2: Output from four different machine learning algorithms on the main questions in the knowledge score

Note: LE_tr17 = Loss assessment; LE_tr14 = Basis risk; LE_tr_10 = Sure payout

Appendix 5.7: Attrition

In the household survey, we had 1409 farmers, however, some information was missing for 5 farmers, who we dropped to give us a sample of 1404. We managed to reach 1331 farmers during the experiment. Because we had a limited sample and since we randomized before going to the field, it was not possible to replace farmers that were not reached. We therefore determine whether the attrition was correlated with the treatment assignment. Appendix Table 5.4 shows that the attrition was independent of the treatment assignment.

Appendix Table 5.4: Attrition

	(1)	**(2)**
Game	−0.102	−0.102
	(0.280)	(0.287)
Narrative	−0.103	−0.174
	(0.326)	(0.334)
Number of observations	1404	1404
AIC	608.3	639.6

Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1

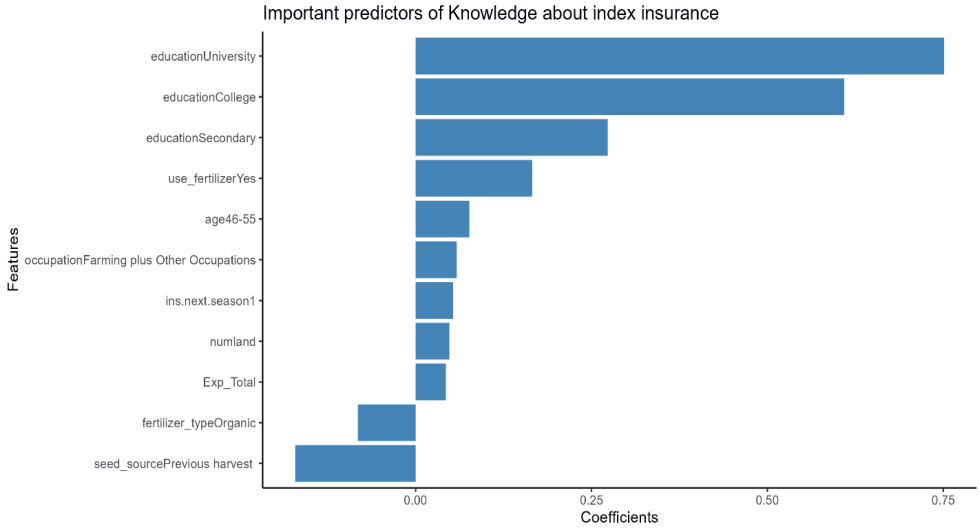
Appendix 5.8: Alternative specification for the demand equation

Appendix Table 5.5: Specification without clustering standard errors

	(1)	**(2)**
Game	−0.101 **	−0.063 **
	(0.044)	(0.026)
Narrative	−0.027	−0.027
	(0.051)	(0.030)
Number of observations.	1331	3993
AIC	5065.3	3509.6

Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1

Appendix 5.9: Main predictors of knowledge from lasso regression

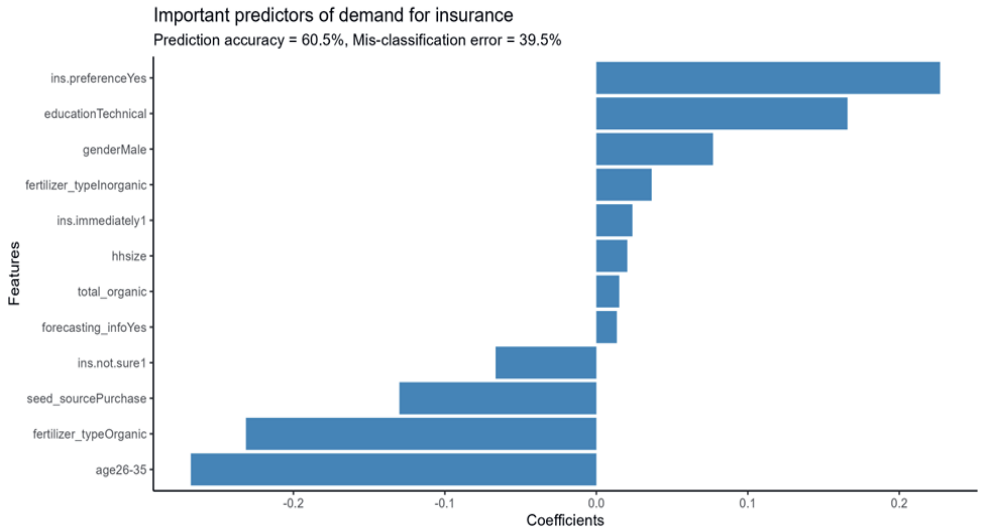


Appendix Figure 5.3: Important features correlating with knowledge

Appendix Table 5.6: Description of the main predictors of knowledge

Variable	Description
University education (*educationUniversity)*	Farmer had university education as the highest level of education (1 = Yes; 0 = Otherwise)
College education (*educationCollege*)	Farmer had college education as the highest level of education (1 = Yes; 0 = Otherwise)
Secondary school education (*educationSecondary*)	Farmer had secondary school education as the highest level of education (1 = Yes; 0 = Otherwise)
Farmer uses fertilizer (*use_fertilizerYes*)	Farmer uses fertilizer (1 = Yes; 0 = Otherwise)
Age 46 – 55 (*age46-55*)	The respondent was within the age bracket of 46 – 55 years old (1 = Yes; 0 = Otherwise)
Farming plus other occupations (*occupationFarming plus Other Occupations*)	Respondent did farming plus other occupations (1 = Yes; 0 = Otherwise)
Interested in insurance for next season (*ins.next.season1*)	A binary variable indicating whether the farmer wanted insurance for the next season or not (1 = Yes; 0 = No)
Pieces of land owned (*numland*)	Number of pieces of land owned by the farmer
Experience with other insurances (*Exp_Total*)	A composite of the number of other insurances a farmer knows (Health insurance, motorbike insurance, and car insurance)
Organic fertilizer (*fertilizer_typeorganic*)	Farmer mainly used organic fertilizer (1 = Yes; 0 = No)
Seed from previous harvest (*seed_sourcePrevious harvest*)	The farmer mainly uses seed from previous season for planting (1 = Yes; 0 = Otherwise)

Appendix 5.10: Main predictors of preference for index insurance from a lasso regression



Appendix Figure 5.4: Important variables correlating with demand for insurance

Appendix Table 5.7: Description of control variables

Variable	Description
Farmer showed interest in insurance (*ins. preferenceYes*)	A dummy showing whether a farmers was interested in insurance at baseline (1 = Yes; 0 = No)
Technical education *(educationTechnical)*	Farmer had technical education as highest level of education (1 = Yes; 0 = No).
Male (*genderMale*)	Binary of whether the farmers was a man or woman (1 = Male; 0 = Otherwise)
Farmer uses inorganic fertilizer (*fertilizer_typeInorganic*)	Farmer mainly uses inorganic fertilizer (1 = Yes; 0 = Otherwise)
Farmer wanted insurance immediately (*ins.immediately1*)	Farmer wanted insurance immediately during baseline (1 = Yes; 0 = No)
Household size (*hhsize*)	Number of individuals in the household
Organic fertilizer amount (*total_organic*)	Amount in Kgs of organic fertilizer the farmer uses on average on an acre of land for maize production
Access to weather information (*focasting_infoYes*)	A binary variable denoting whether the farmer receives weather information (1 = Yes; 0 = Otherwise)
Not sure when to take insurance (*ins.not.sure1*)	A binary showing whether the farmer was not sure when to take insurance (1 = Yes; 0 = No)
Organic fertilizer (*fertilizer_typeorganic*)	Farmer mainly used organic fertilizer (1 = Yes; 0 = No)
Purchases seed (*seed_sourcePurchase*)	The farmer mainly purchases planting seed Main source where the farmer sources seed (1 = Yes; 0 = Otherwise)
Age 25 - 35	The respondent was within the age bracket of 25 – 35 years old (1 = Yes; 0 = Otherwise)

Appendix 5.11: Controlling for unbalanced variables in our main regression analysis

As a robustness check, we assess whether our results are stable when we (do not) include unbalanced variables in our main regressions. The unbalanced variables in the estimation of the effect of the game on knowledge were whether a farmer had a college education, whether the farmer used fertilizer, and whether the farmer did farming plus other occupations (see Table 5.11 of the main text). Unbalanced control variables for the demand equation were gender and interest in insurance at baseline. We present these results in Appendix Table 5.8. Columns 1 and 2 are the knowledge regressions. Column 1 doesn't include the unbalanced covariates while column 2 includes the covariates. Columns 3 and 4 are the demand regressions. Column 3 does not include the unbalanced covariates while column 4 includes the unbalanced variables. The results show that the coefficients are stable across the four estimations.

Appendix Table 5.8: Controlling for unbalanced covariates

	(1)	(2)	(3)	(4)
Game	0.992***	0.973***	−0.105***	−0.101***
	(0.056)	(0.055)	(0.039)	(0.038)
Narrative	0.867***	0.838***	−0.021	−0.012
	(0.063)	(0.062)	(0.043)	(0.044)
Unbalanced controls	No	Yes	No	Yes
Other controls	Yes	Yes	Yes	Yes
Number of observations	1331	1331	1331	1331
Adjusted R2	0.386	0.416		
AIC	3067.9	3004.0	4971.9	4958.4

Significance: *** = $p < 0.01$; ** = $p < 0.05$; * = $p < 0.1$

Appendix 5.12: Model selection for sensitivity analysis

The model combination for sensitivity analysis in the mediation package is limited to OLS and either probit or logit models (Tingley et al., 2014). This means that we are not able to conduct a sensitivity analysis to test whether the sequential ignorability assumption was violated using our preferred models (interval regression, or OLS with clustered standard errors). We explore the

results from different specifications and present the results in Appendix Table 5.9. The linear mixed model with long data (1) captures the repeated nature of the outcome variable for each household (we do not cluster standard errors at sublocation level). For the OLS model (2), the linear mixed model with clustered standard errors (3), OLS with robust errors (4), and linear probability model (5), we lose some data on the dependent variable because we only consider choices at Ksh. 150 offer. Model (6) represents results from the interval regression (our preferred model). In model (2) and model (6), we cluster standard errors at sublocation level. We do not see much of a difference in the results. To have an idea of whether our data violates the sequential ignorability assumption, we used model (5).

Appendix Table 5.9: Alternative specifications of the outcome regression for sensitivity analysis

	(1)	(2)	(3)	(4)	**(5)**	(6)
Game	0.021	0.040	0.041	0.037	**0.042**	0.026
	(0.036)	(0.045)	(0.045)	(0.044)	**(0.044)**	(0.061)
Narrative	0.005	−0.010	−0.010	−0.003	**0.002**	0.001
	(0.032)	(0.040)	(0.040)	(0.039)	**(0.039)**	(0.052)
Knowledge	−0.041***	−0.029*	−0.029*	−0.048***	**−0.049*** **	−0.053**
	(0.012)	(0.016)	(0.016)	(0.016)	**(0.015)**	(0.022)
10% basis risk	−0.040	−0.065	−0.064	−0.037	**−0.048**	−0.080
	(0.037)	(0.047)	(0.047)	(0.046)	**(0.046)**	(0.065)
15% basis risk	−0.082**	−0.095**	−0.093**	−0.089*	**−0.098** **	−0.134**
	(0.036)	(0.046)	(0.046)	(0.046)	**(0.045)**	(0.057)
Constant	0.590***	0.366***	0.370***		**1.482*** **	4.426***
	(0.103)	(0.130)	(0.131)		**(0.126)**	(0.181)
Additional controls	Yes	Yes	Yes	Yes	**Yes**	Yes
Number of observations	3978	1326	1326	1326	**1326**	1326
R2		0.030		0.123	**0.033**	
AIC	3550.0	1874.5	2004.7	1666.8	**1798.4**	5056.5

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1.

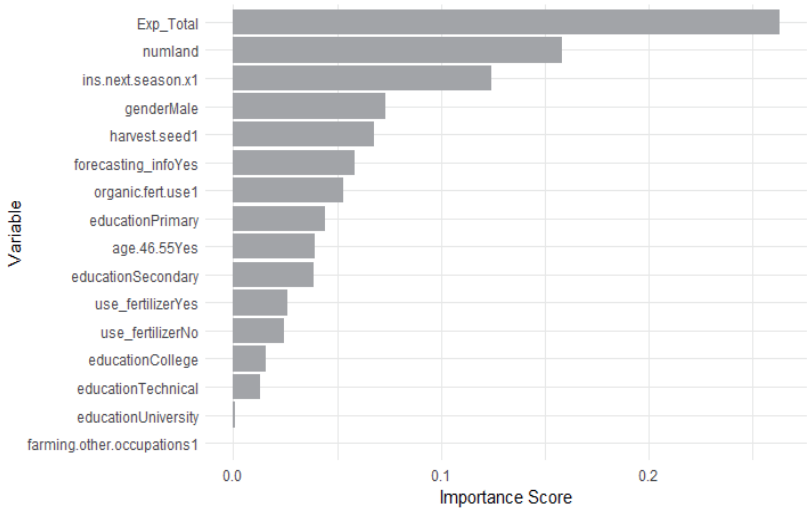
Appendix 5.13: Heterogeneous treatment effects

It is likely that the effect of the game knowledge and demand for the insurance voucher is not homogeneous—it might be determined by some observed farmer characteristics that either influence how different sub-groups interact with games or correlate with pre-treatment perceptions of index insurance. For example, men are known to be more competitive than women (Lénárd et al., 2024), which might influence factors such as interest in a game (how long someone wants to spend in a game, and frequency of playing the game), and how they interact with games and game elements. This is likely to influence learning outcomes. Similarly, the effect of new information is likely to depend on the experience(s) with, and prior knowledge about index insurance. Based on the nature of experience (positive or negative), demand can either increase or decrease. Though men are not more likely to purchase insurance than women farmers (Timu et al., 2023), there is evidence for differences in index insurance product preferences between men and women (Akter et al., 2016).

Usually, selection of relevant variables is guided by literature. The downside of this approach is that any variable known to correlate with the outcome is a candidate thus challenging (biasing) the selection. In our case, we "allow the data to speak" by using machine learning to identify variables in our data set likely to contribute to heterogeneous treatment effects. We use the causal forest algorithm to achieve this goal (Wager & Athey, 2018), the aim being not to estimate the heterogeneous treatment effects as it is usually the application, but rather to identify important variables. We then use these variables in the next steps to assess whether we observe significant heterogeneous treatment effects in our sample using a regression framework.

Appendix 5.14: Heterogeneous treatment effect of the intervention on knowledge about insurance

Important variables likely to cause heterogeneity in the effect of our intervention on knowledge were experience with other insurance (Exp_Total), household size (hhsize), and amount of organic fertilizer used (total_organic) (Appendix Figure 5.5).



Appendix Figure 5.5: Important variables contributing to heterogeneity in treatment effects on knowledge

The results from the regression analysis are shown in Appendix Table 5.10. We do not see any effect when we interact the treatment dummy with experience with other insurances and gender. We see a significant positive effect between the treatment and the number of pieces owned by the farmer. However, this effect cancels out when we interact the variable with the treatment dummy. While showing interest for insurance for the next season had a significant negative effect to learn about insurance, this group of farmers were more receptive to the information intervention (for both the Game and Narrative treatments), which is plausible. The farmers were able to accumulate more knowledge about insurance, which is plausible since they wanted insurance for the next season.

Appendix Table 5.10: Heterogeneous treatment effect of intervention on knowledge

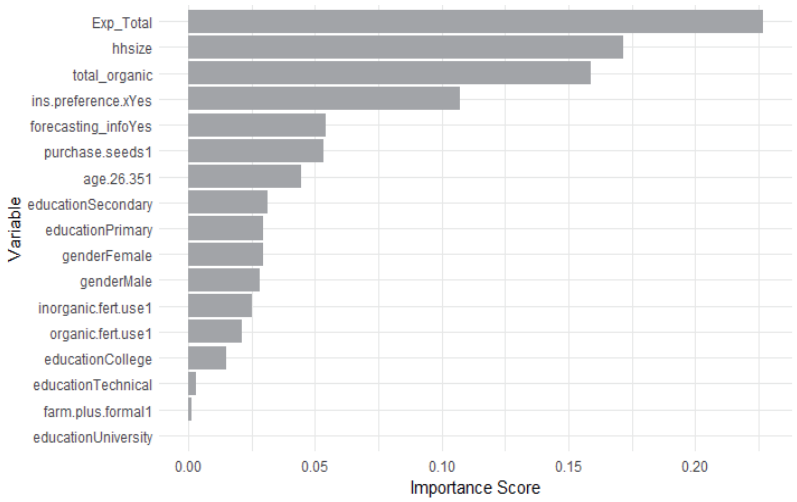
	(1)	(2)	(3)	(4)
Game	1.008***	1.140***	0.884***	1.019***
	(0.081)	(0.101)	(0.067)	(0.072)
Narrative	0.837***	1.026***	0.732***	0.880***
	(0.094)	(0.115)	(0.079)	(0.083)
Experience with other insurances	0.047*	0.036***	0.037***	0.038***
	(0.026)	(0.013)	(0.013)	(0.013)
Pieces of land owned	0.020	0.086**	0.020	0.020
	(0.018)	(0.037)	(0.018)	(0.018)
Primary education	0.293***	0.296***	0.289***	0.292***
	(0.088)	(0.088)	(0.089)	(0.088)
Interest in insurance for next season	0.042	0.041	−0.139	0.041
	(0.045)	(0.045)	(0.093)	(0.045)
Male	0.060	0.058	0.059	0.138
	(0.045)	(0.045)	(0.045)	(0.090)
Game × Experience with other insurances	−0.016			
	(0.030)			
Narrative × Experience with other insurances	−0.005			
	(0.034)			
Game × Pieces of land owned		−0.079*		
		(0.042)		
Narrative × Pieces of land owned		−0.095**		
		(0.047)		
Game × Interest in insurance for next season			0.233**	
			(0.110)	
Narrative × Interest in insurance for next season			0.247*	

	(1)	(2)	(3)	(4)
			(0.126)	
Game × Male				−0.100
				(0.110)
Narrative × Male				−0.112
				(0.124)
Number of observations	1331	1331	1331	1331
Adjusted R2	0.422	0.424	0.425	0.423
AIC	2992.5	2987.6	2987.0	2991.7

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Control variables include household size, interest in insurance for next season, number of pieces of land owned, use of organic fertilizer, gender (male), age 46 – 55, education, use seeds from previous season, access to weather information, and doing farming plus other occupations. The standard errors are robust, clustered at sub-location level. We control for enumerator effects.

Appendix 5.15: Heterogeneous treatment effect of the game on demand for insurance

The important variables are experience with other insurances (Exp_Total), household size (hhsize), and total organic fertilizer used (total_organic) (Appendix Figure 5.6).



Appendix Figure 5.6: Important variables causing heterogeneous treatment effects of the game on demand for insurance

Next, we test whether these variables cause variations in the treatment effect (Appendix Table 5.11) using a regression approach. We do not find evidence for the presence of heterogeneous treatment effects on demand.

Appendix Table 5.11: Heterogeneous treatment effect of the game on demand for insurance

	(1)	(2)	(3)
Game	−0.144***	−0.024	−0.105***
	(0.050)	(0.085)	(0.038)
Narrative	−0.014	−0.014	−0.015
	(0.044)	(0.043)	(0.044)
Experience with other insurances	−0.003	0.007	0.007
	(0.011)	(0.008)	(0.008)
Household size	0.005	0.013	0.005
	(0.006)	(0.010)	(0.006)
Amount of organic fertilizer	0.008*	0.008*	0.007*
	(0.005)	(0.005)	(0.004)
Game × Experience with other insurances	0.020		
	(0.016)		
Game × Household size		−0.015	
		(0.014)	
Game × Amount of organic fertilizer used			0.003
			(0.015)
Controls	Yes	Yes	Yes
Number of observations	1331	1331	1331
AIC	4959.4	4959.5	4960.6

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Control variables include household size, interest in insurance at baseline, use of organic fertilizer, amount of organic fertilizer, gender (male), age 26 – 35, education, purchases seed, access to weather information, wanted insurance immediately, farmer was not sure when they would need insurance. The standard errors are robust, clustered at sub-location level. We control for enumerator effects.

Chapter 6

Information and Food Quality in Informal Markets: Experimental Evidence from Kenya

Abstract

In informal markets with weak regulation and incomplete information, unobservable food quality attributes such as safety are often undersupplied. Observable traits can serve as proxies for these attributes, but market actors often lack knowledge of these correlations. We conducted a randomized controlled trial in 90 rural maize markets in eastern Kenya to test whether a six-week information campaign linking kernel appearance to aflatoxin contamination, a major but unobservable food safety risk, affected consumer demand and trader supply. Three weeks after the campaign, maize in treatment markets showed improvements in observable quality, accompanied by behavioral responses among consumers and traders, including increased checking of kernel integrity and marginal sorting of damaged kernels. Price premia for higher-quality maize did not emerge; instead, sales volumes declined, driven primarily by reduced sales of poor-quality maize. These effects had attenuated by the second follow-up, approximately two months later, as new maize entered the markets. Results suggest that low-cost information can induce short-run improvements in food quality in informal markets; sustaining these gains likely requires repeated campaigns or complementary incentives.

Key words: Food safety; Informal markets; Aflatoxin; Information; Framing; Food Quality

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1. Introduction

Informal markets[32] are integral to food systems in developing countries, serving as the primary source of food for consumers, linking rural producers to buyers, and providing employment for a wide range of actors (Giroux et al., 2021). Yet these markets often operate outside formal regulation, with weak enforcement of food safety standards (Roesel & Grace, 2014), limited infrastructure (de Janvry & Sadoulet, 2020), and high transaction costs (Aker, 2010), as well as fragmented supply chains linking numerous small producers to intermediaries and aggregators, and substantial heterogeneity in bargaining power across market actors (Abate et al., 2021; Bergquist & Dinerstein, 2020; Burke et al., 2019). A defining feature is incomplete information: market actors cannot easily assess product attributes that are not directly observable or that require specialized technologies to test. Under such conditions, markets risk becoming "markets for lemons" (Akerlof, 1970; Anissa et al., 2021; Bold et al., 2022), where low-quality products dominate, incentives to supply quality remain weak (Hoffmann et al., 2019), and overall welfare gains are reduced.

One particularly important but largely unobservable food quality attribute is food safety. Despite its significance for public health and economic growth, food safety is often not prioritized in low-income country contexts (Karanja et al., 2022). Low consumer awareness of health risks, combined with limited willingness to pay for safer foods, leads to chronic underinvestment in safety by market actors (Hoffmann et al., 2019). While regulations exist, they are weakly enforced

[32] Informal markets refer to trading spaces where actors operate without formal registration, licensing, or enforcement of regulations related to taxation, labor, or health standards. They include street vendors, open-air markets, and small-scale retail outlets that are often critical for food access and rural livelihoods but typically lack adequate infrastructure and oversight (Grace, 2023; Roesel & Grace, 2014). Other names have been used to describe informal markets such as wet markets, open-air markets, public markets, traditional markets (Davies et al., 2022).

due to limited institutional capacity and the widespread informality of food markets (Jaffee et al., 2019). As a result, the global burden of foodborne diseases is disproportionately concentrated in low- and middle-income countries, which account for about 75% of cases (Grace, 2023).

Rising urbanization and incomes are expected to increase demand for safe food (Ortega & Tschirley, 2017). Stimulating consumer demand through information could "pull" supply toward safer products (Lin et al., 2024). Conversely, traders and other market actors may invest in food safety if they perceive business-related benefits, such as reputation gains or higher profits (Hoffmann & Moser, 2017). The central challenge is how to create incentives for the supply of safe food in markets where regulations are weak and the cost of testing often exceeds the value of a typical transaction (Hoffmann, Mutiga, et al., 2021).

In such contexts, observable traits—such as kernel integrity, color, or visible damage—offer a promising alternative. Recent work has emphasized the role of observable product attributes that are correlated with unobservable quality, such as visual appearance or physical integrity (Bold et al., 2022; Hoffmann, Mutiga, et al., 2021). If buyers can be informed that these attributes signal safety, demand for quality may increase, potentially inducing suppliers to upgrade quality even in the absence of formal certification. Whether such information changes behavior and, ultimately, food safety outcomes is an open question, the focus of our paper.

This paper studies whether such an information-based mechanism can operate in informal maize markets in Kenya, where aflatoxin contamination represents a major but largely unobservable food safety risk. Chronic exposure to aflatoxins is associated with liver cancer, immune suppression, and child stunting, while acute exposure can be fatal (IARC, 2015; Azziz-Baumgartner et al., 2005). Numerous studies document aflatoxin contamination in both formal and informal maize markets in Kenya (Hoffmann, Mutiga, et al., 2021; Barasa et al., 2023).

Importantly, prior research shows that visible grain damage—such as broken or insect-damaged kernels—is correlated with aflatoxin risk, yet consumers are largely unaware of this relationship and do not reward higher-quality grain with price premia (Hoffmann, Mutiga, et al., 2021).

If consumers were informed that kernel integrity signals safety, they might begin to demand this attribute. Traders, recognizing this demand, could respond by sourcing higher-quality maize or improving quality through practices such as sorting. Because kernel integrity is influenced by production conditions (e.g., drought stress) and post-harvest practices—such as shelling method (beating versus machine shelling) and storage conditions, particularly where insect damage occurs—it is a trait that producers and traders can feasibly improve if incentives exist. In principle, this could generate a price premium for higher-quality maize and trigger supply-side investment and safer consumption.

We test whether providing information about this correlation to both consumers and traders can shift market outcomes. We conducted a randomized controlled trial in 90 rural maize markets in Eastern Kenya, randomly assigning markets to receive a six-week information campaign or to serve as controls. In treatment markets, trained enumerators repeatedly communicated three messages: what aflatoxins are, their health consequences, and the link between kernel integrity and aflatoxin contamination. To study how the salience of food safety risk information matters, treatment markets were further randomized to receive either positively framed (gain-focused) or negatively framed (loss-focused) messages. Outcomes were measured using trader and consumer surveys and through physical inspection of maize samples collected at baseline and at two post-intervention follow-ups.

Our intervention simultaneously targeted consumers and traders to align demand and supply, addressing a coordination failure that may undermine food safety investments in informal

markets. Traders may invest in quality if they anticipate gains through reputation or profits, but such incentives depend on consumers' ability to recognize and value safety-related attributes like kernel integrity. Without informed consumers, traders must expend effort and incur additional costs to communicate quality improvements, weakening their incentives. Conversely, informing consumers alone may raise demand, but without supply responses, market outcomes may remain unchanged (S. Kariuki et al., 2025). By targeting both sides, the intervention reduced information asymmetries and transaction costs, creating a push–pull mechanism that strengthens incentives and increases the likelihood of quality improvements.

We document five main findings. First, three weeks after the intervention, maize sold in treatment markets exhibited modest but statistically significant improvements in observable quality: treated maize samples contained fewer damaged kernels and were substantially less likely to exceed a low-quality threshold. Second, despite these quality improvements, average maize prices did not increase and, if anything, declined slightly, and we find no evidence of price premia for higher-quality grain. Third, total maize sales volumes declined in treatment markets, driven primarily by reduced sales of visibly poor-quality maize. Fourth, we document behavioral responses by both traders and consumers, including increased checking of kernel integrity by both groups and marginal sorting or removal of damaged kernels by traders. Fifth, while some consumer and trader behaviors persisted, quality improvements faded by the second follow-up, indicating that information alone generates short-run effects that are difficult to sustain without reinforcement or complementary incentives. Together, these patterns suggest that the intervention induced avoidance of visibly poor-quality maize rather than sustained quality upgrading or product differentiation, with traders making marginal adjustments to meet minimum acceptability thresholds rather than investing in higher-quality segments

Our study contributes to literature in three ways. First, it contributes to the literature on whether reducing information failures about unobservable food attributes can create demand for these attributes and thus enable markets for quality and safety to emerge (Akinwehinmi et al., 2022; Ariong et al., 2024; Hoffmann, Moser, et al., 2021; S. W. Kariuki & Hoffmann, 2022; Magnan et al., 2021; Nindi et al., 2023; Ricker-Gilbert et al., 2025). Like some of these studies, we focus on informal markets, which remain the primary food source for most consumers in developing countries but where regulation is weakest. However, while prior studies have focused on supply-side interventions at the farm level (e.g., Hoffmann, Moser, et al., 2021; Magnan et al., 2021), we target both consumers and traders in informal markets (both demand and supply). Targeting the market actors is especially important in the context of informal markets because part of the quality deterioration may occur post-harvest rather than at the point of production (Prieto et al., 2021). Many of the studies that focus on the demand side are lab-in-the-field studies which, while providing useful insights, may produce biased estimates (Hoffmann et al., 2019). Lastly, we show that in markets with rigid pricing institutions (Ariong et al., 2024), information can generate economically meaningful responses through quantities and quality composition even in the absence of price premia, highlighting an underappreciated adjustment margin in informal markets. Third, by comparing positive and negative framing, we shed light on how the salience of economic information shapes responses among traders and consumers, with implications for the design of low-cost food safety interventions.

Taken together, our findings show that while simple scalable information campaigns can improve food safety in the short run, sustaining these gains likely requires repeated engagement or complementary mechanisms that strengthen incentives for quality upgrading. These results have implications for the design of food safety policies in settings where formal regulation and

certification are infeasible, but where observable product attributes provide a potential basis for market-driven improvements in quality.

The remainder of the paper is organized as follows. Sections 2 and 3 describe the study context, sample, and experimental design. Section 4 outlines the estimation strategy. Section 5 presents the results, and Section 6 discusses implications and concludes.

2. Study context: Maize markets in Kenya

Maize is a dietary and economic staple in Kenya, serving both as a primary source of calories and as a key income-generating crop for rural households. Per capita maize consumption in Kenya is among the highest in sub-Saharan Africa, estimated at approximately 62 kg per person per year (De Groote, 2023). Maize is consumed either as whole grain or processed into flour. *Ugali*, a stiff maize porridge, remains a dietary mainstay across the country. Maize in Kenya frequently contains aflatoxin levels that exceed regulatory limits (Hoffmann, Mutiga, et al., 2021). Given this high level of consumption, even modest levels of contamination can result in substantial population-wide exposure to food safety risks.

Kenya's maize marketing system is characterized by a sharp dualism between a relatively small formal sector and a large informal sector. The formal sector consists primarily of industrial millers producing branded flour. These firms increasingly test maize for aflatoxins as part of procurement processes, motivated by regulatory requirements, reputational concerns, and access to higher-income consumers (Hoffmann & Moser, 2017). Grain that fails to meet safety standards is often rejected and diverted away from these channels.

In contrast, the informal market largely consists of unbranded maize grain sold directly to consumers or to small-scale traders who resell in smaller quantities. Consumers purchasing from these informal channels typically cook the grain directly or take it to local hammer mills (*posho*

mills) for flour processing. These informal markets operate with minimal regulatory oversight, high transaction costs, limited infrastructure, and traders sell largely unbranded and undifferentiated products.

Maize entering informal markets originates from numerous smallholder farmers and passes through multiple intermediaries, including brokers and aggregators, before reaching retail traders and consumers. Aflatoxin testing is rarely conducted either at the farm gate (prior to aggregation) or after aggregation, leaving contamination largely unobserved along the value chain. Prior research shows that visible grain damage—such as broken or perforated kernels—is strongly correlated with aflatoxin contamination (Hoffmann, Mutiga, et al., 2021). However, consumers are generally unaware of this correlation and do not systematically reward higher-quality grain with price premia, limiting incentives for traders to sort or source higher-quality maize. By contrast, visibly discolored maize is widely perceived by consumers as low quality and risky and therefore tends to fetch lower prices. The formal sector's use of "test-and-reject" mechanisms often diverts contaminated maize into the informal sector, concentrating food safety risks among low-income consumers who rely on these markets for affordability and accessibility. A recent study found that unbranded flour from informal markets contains significantly higher aflatoxin levels than branded flour produced by formal millers (Barasa et al., 2023).[33] Given the scale and importance of informal markets in meeting consumer demand, they represent a critical locus for public health interventions aimed at reducing aflatoxin exposure.

[33] While this could be due to quality sorting, it may also be the result of the removal of the outer part of the grain (bran and germ), which may have larger contamination levels than the interior parts (Prietto et al., 2015).

3. Study design

3.1. Population and sample

Our population consists of traders and consumers in informal grain markets in Eastern Kenya, a known aflatoxin hotspot in Kenya (S. W. Kariuki & Hoffmann, 2022). To identify eligible markets, we first obtained a list of all the markets in Meru County, along with key contact people for each (in some cases, area chiefs), from the county's Department of Trade. We then conducted a brief phone survey with these contacts to verify market and village names, main market days, and the estimated number and type of retail maize traders. Markets where the contact person could not be reached or where no maize traders operated were excluded, resulting in a final sample of 90 markets for the study.

3.2. Experimental design and interventions

Our study consisted of two experimental groups: a control group and an information treatment group. The treatment group was further divided into two equal subgroups, which randomly received either positively or negatively framed information on the effect of aflatoxin on human health risk and child growth. In treatment markets, trained enumerators delivered three key messages to both traders and consumers: an explanation of what aflatoxin is, the health risks associated with consuming aflatoxin-contaminated maize, and the link between visible maize quality, specifically the integrity of the outer kernel and the likelihood of aflatoxin contamination. Intervention scripts are provided in Appendix 1.

In markets assigned to the negative framing treatment, both traders and consumers received information emphasizing the harmful health effects of consuming aflatoxin-contaminated maize, including increased risks of liver cancer and stunting in young children. Messages highlighted that maize with more damaged kernels was more likely to be contaminated and urged individuals to

avoid such maize to reduce aflatoxin exposure. In contrast, markets assigned to the positive framing treatment received messages that focused on the health benefits of consuming aflatoxin-safe maize, including a reduced risk of liver cancer and healthier growth outcomes for children. These messages framed maize with fewer damaged grains as safer and encouraged consumers to seek out such maize.

The intervention was administered by trained field assistants fluent in the local language. These assistants visited the markets during peak hours (typically one or two days each week) and delivered information directly to traders and consumers. To maximize reach, they positioned themselves at key entry and exit points of the markets. The information campaign was also supported with flyers and posters (see Appendix 2): flyers were distributed to consumers and left at traders' shops for distribution by the traders to consumers coming to buy maize, while posters were displayed at strategic locations around the market, including in the shops of participating traders. The campaign was implemented weekly in each market over a six-week period starting from the second week of September 2022 to the last week of October 2022 (see Figure 1). This coincides with the planting period of the main season, which runs from October to March. To expand coverage beyond the markets, field assistants also intercepted people leaving nearby churches located within a one-kilometer radius of the market centers.

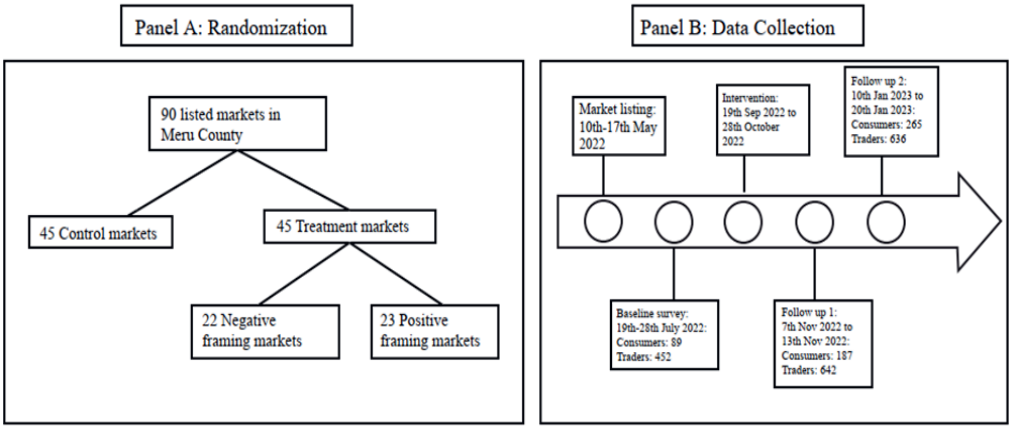


Figure 3: Randomization and timelines

3.3. Randomization

Randomization into either the treatment or control groups was conducted at the market level, with each market having a 50% chance of being assigned to either group. Within the treatment group, markets were further randomized to either a "positive" or "negative" framing of the information, with equal probability (50%). Randomization at the market level was used to minimize potential spillovers, as interactions (trader-to-trader, trader-to-consumer, and consumer-to-consumer) are more likely to occur within markets than across them. To improve balance across groups, treatment assignment was stratified by sub-county and by a binary indicator for market size, defined as 1 if the number of maize retailers in a market was above the sample mean, and 0 otherwise.

3.4. Data and data sources

Data sources comprise three rounds of surveys with traders and consumers: one pre-intervention (baseline) and two post-intervention rounds (follow-up 1 and follow-up 2). In each round, we

collected 100 grams of maize from each quality type available with the trader, for analysis of the physical attributes of interest. [34]

The baseline survey was conducted in July 2022, just prior to the implementation of the intervention. We aimed to interview six retail maize traders per market—three operating from shops or kiosks and three selling in open-air spaces. Enumerators first conducted a quick count of all eligible traders in each category. If there were 6 traders or fewer, all were interviewed. For more than six traders, every second trader was interviewed until three were reached for each category of traders (shop/kiosk and those selling in open-air spaces). Sampling always began from one end of the market to ensure consistency. Table 6.1 shows the sample sizes for each data collection round.

Trader data covered demographic characteristics, maize sourcing and quality assessment practices, pricing and sales behavior, maize handling practices, and awareness, attitudes, and self-reported practices related to aflatoxin contamination. Consumer data covered demographics, maize purchasing behavior, quality assessment practices, intended use of purchased maize, knowledge, beliefs, and willingness to pay related to aflatoxins. We used the same procedure and survey tools to collect data at both follow-ups.

Follow-up 1 was conducted in November 2022, corresponding to the lean season, while follow-up 2 was conducted in January 2023, corresponding to the harvest season. We targeted all traders in each market during the follow-up surveys, with a maximum of 15 traders in markets that had more than 15[35]. In such cases, we randomly sampled the traders systematically, selecting every third trader until we reached the required number. Similarly, in each market, we targeted three

[34] Traders were informed that the maize was for research. We incentivized the traders to give us the 100 grams by buying at the prevailing market price for a kilogram of maize.
[35] At follow-up, we opted to interview all traders in each market (up to a maximum of 15 in very large markets), motivated by power considerations since at least 25% of markets in our sample had five traders or fewer. The average market size consisted of 10 traders, with a median of seven.

consumers who came specifically to buy maize. We applied the same systematic sampling approach, interviewing every third eligible consumer after the previous one, aiming for up to 3 consumers per market. Data from the follow-up surveys were used to construct the main and intermediate outcomes for estimating the intention-to-treat (ITT) effects of the intervention.

Table 6.1. Sample sizes

	Baseline	Follow-up 1	Follow-up 2
Markets	90	89	84
Total number of traders	452	703	711
Traders consented to participate in study	447	642	636
Traders with maize samples	425	520	492
Number of maize samples collected	454	587	531
Consumers	89	187	265

Notes: The number of maize samples collected differs from the number of traders because not all traders had maize samples at the time the survey was conducted and because others had more than one maize sample.

3.5. Assessment of maize quality

Quality assessment involved a detailed inspection of maize grains using three indicators: (i) broken kernels, (ii) insect perforation, and (iii) discoloration. The inspection was conducted at Kiboko, one of the Kenya Agricultural and Livestock Research Institute (KALRO) centers and was independently performed twice by two different research assistants to minimize errors. The assistants separated, counted, and weighed the damaged grains as well as the total number of grains in each sample. Grain quality was expressed as the proportion of grains with a damaged kernel (either physical damage or broken kernels or insect perforation) relative to the total number of grains in the 100-gram sample. For the analysis, we also used (in addition to the continuous variable) a dummy variable, 0 if the proportion of grains with damaged kernels was below 10%, and 1 otherwise.

3.6. Descriptive statistics

3.6.1. Markets, traders and maize quality at baseline

Table 2 summarizes market and trader characteristics, and the quality of maize at baseline. Markets were generally small, with a mean of 10 traders and a median of 7, though the largest market had more than 50 traders. At least one quarter of markets comprised five or fewer traders. Markets were dominated by traders operating in permanent or semi-permanent structures, as the share of open-air traders averaged only 10% per market.

The average age of traders was 42 years, with an average of 7 years of experience in the maize business. Many of the traders (83%) were female, which is in line with the evidence that informal trade in low-income countries is dominated by women (Pyburn et al., 2023). Most traders had attained primary education (81%) and operated from a shop or kiosk (75%).

Traders reported selling an average of 27 kilograms of maize on the previous market day. Regarding maize of different qualities and trading practices, approximately 7% of traders reported having more than one type of maize in stock, although only 2.5% engaged in price differentiation based on quality. Regarding sourcing practices, approximately 60% reported sourcing maize from other traders in different markets within the county, 43% reported sourcing directly from local farmers, and 14% reported producing maize themselves.

On average, 11% of the kernels in a 100-gram maize sample were damaged at baseline, and 42% of the samples collected contained more than 10% damaged kernels (Table 6.2). The average price of maize was Ksh. 73 per kilogram, and traders reported selling an average of 53 kilograms of maize on the previous market day[36].

[36] A market day is a designated day or days in a week when traders and consumers gather in a certain market space to exchange good and services.

Table 6.2: Market, trader, and maize quality characteristics at baseline

	N	Mean	SD	Median
Market characteristics				
Number of maize traders	90	10.00	9.00	7
Share of open-air traders	90	0.11	1.14	0.08
Trader characteristics				
Age of the retailer in years	431	41.80	12.70	40
Years in the maize retail business	443	7.30	7.90	5
Retailer is male	447	0.17	0.38	0
Retailer had primary level education	447	0.81	0.40	1
The trader operated a shop/kiosk	447	0.75	0.43	1
Total amount sold on the last market day	447	27.40	44.30	10
Trader had more than one maize type	447	0.07	0.25	0
Trader reports that they sort maize	447	0.03	0.17	0
Source of maize				
Own production	447	0.13	0.33	0
Another trader in the same market	447	0.15	0.36	0
Another trader in a different market but in the same county	447	0.60	0.49	1
Another trader in a different market (another county)	447	0.08	0.27	0
Farmers in the same area	447	0.43	0.50	0
Farmers in a different village	447	0.09	0.28	0
Maize quality (maize sample characteristics)				
Proportion of damaged kernels	454	0.11	0.09	
Above 10% damaged	454	0.42		
Average price of maize on the day of the interview (KES per kg)	454	73.50	9.00	70

3.6.2. Consumer characteristics at baseline

We focused on consumers purchasing maize from shops and open-air markets. Although general awareness of aflatoxin was relatively high (71%), fewer than 2% of consumers were aware of its correlation with kernel integrity (Table 6.3). About 68% of the consumers had attained primary

education or higher, and the average age was 40 years. A large majority (85%) were maize farmers, and only 16% of the respondents were male.

Table 6.3: Consumer summaries

Variable	Mean	SD
Awareness about aflatoxin	0.71	
Awareness about the correlation between kernel integrity and aflatoxin	0.02	
Knowledge of aflatoxin and effects on health	1.13	0.94
Age of consumer in years	40.10	13.10
Consumer had above primary level education	0.69	
Consumer is a maize farmer	0.85	
Consumer considers kernel integrity at purchase	0.27	
Consumer is male	0.16	

Notes: We do not report SD for dummy variables, and N = 89.

3.7. Balance checks

We conduct balance checks using the sample of traders for whom we have follow-up data, as this constitutes our main analysis sample. At the trader level, we use demographic characteristics—specifically age, education, and experience in the maize business. Since maize quality, price, and sales volume data were not available for the full analysis sample prior to the intervention, we use baseline data to construct market-level averages of these variables. Appendix Table 6.1 reports the p-values from tests of mean equivalence, first between treatment and control groups, and then across each treatment and control subgroup. The analysis sample is generally well balanced: only two of the 43 tests yield p-values below 0.10. Results for the follow-up two analysis sample show a similar pattern.

4. Empirical strategy

If consumers are aware of the health risks associated with aflatoxins and understand the visual cues linked to contamination, they are more likely to demand maize that exhibits these desirable

qualities. In turn, traders recognizing that consumers rely on observable traits as proxies for safety may respond by supplying maize that meets these standards. Traders might also use this information strategically, either to strengthen customer relationships or to increase profits. This could enable them to charge higher prices for better-quality maize or, at the very least, to sell more relative to those offering poorer-quality grain. Guided by this logic, our analysis first examines whether the intervention affected three main outcomes: maize quality, maize prices, and sales volumes. Second, we assess the effect of the intervention on trader and consumer outcomes, which in our theory of change, are the drivers of improvements in quality, price, and sales[37].

Maize quality was measured using samples collected during both follow-up surveys. The price outcome is measured as the trader-reported price of the maize sample at the time of interview, expressed as the price per kilogram in Kenyan Shillings (KES). Sales volume is measured at the trader level as the total quantity of maize sold over the past three days, presented in kilograms and as an inverse hyperbolic sine (IHS) transformation.

Equation (6.1) is estimated for outcomes measured at the sample level (maize quality and price). We estimate two types of regressions: an ordinary least squares (OLS) regression for the continuous quality measures and prices[38], and a linear probability model (LPM) for the binary quality indicators.

[37] These outcomes were prespecified in our pre-analysis plan registered in the AEA RCT registry Does information stimulate demand for and supply of high-quality food

[38] Treatment is randomly assigned, implying that OLS estimates of the treatment effect are unbiased even when some traders contribute multiple observations. Standard errors are clustered at the trader level to account for within-trader correlation. Given the small share of traders with more than one maize sample, concerns about over-rejection are limited. Panel specifications with trader fixed effects do not alter identification but may improve precision by absorbing time-invariant trader heterogeneity.

$$X_{Csij} = \alpha + \beta_1 Treat_j + \beta_2 M_{ij} + \beta_3 M_j + \varepsilon_{ij} + \varepsilon_{Csij} \quad (6.1)$$

X_{Csij} represents the outcome for sample *Cs* collected from trader *i* in market *j*. $Treat_j$ denotes the treatment status of market *j*. M_{ij} denote trader level controls including age of the trader in years, gender of the trader, level of education, experience in trading business, and an indicator if the trader was interviewed at baseline; while M_j are the market level controls, including average quality of the maize samples collected at baseline, average price of the maize at baseline, total sales volume at baseline, and share of open-air kiosks in the market. We also include strata dummies and cluster standard errors at the trader level. We test if $\beta_1 = 0$ (i.e., intervention had no effect on quality).

Equation (6.2) is estimated for the outcomes measured at the trader level (i.e., sales volumes).

$$V_{ij} = \alpha + \gamma_1 Treat_j + \gamma_2 M_{ij} + \gamma_3 M_j + \varepsilon_j + \varepsilon_{ij} \quad (6.2)$$

The arguments are as in equation (6.1).

Our analysis sample comprises all traders present during the follow-up surveys, since the intervention was implemented at the market level and all traders in treated markets were exposed. While entry by new traders between survey rounds could potentially affect the composition of traders observed at follow-up, our maintained assumption is that traders respond to local demand conditions. Accordingly, it is plausible that new traders operating in treated markets adjust their behavior in response to changes in consumer behavior induced by the intervention.

Similarly, for the analysis of consumer-level outcomes aimed at studying mechanisms, we include consumers who were present in the markets during the follow-up surveys, rather than restricting the sample to consumers interviewed at baseline. Given the predominantly rural setting,

in-migration into study villages is likely limited; nevertheless, any consumer-level effects we report may be conservative and should be interpreted as lower-bound estimates.

5. Results

In this section, we first present the effects of the intervention on maize quality and then the results related to whether improved quality influenced maize prices and volume of maize sold. We then present results on the effect of the intervention on consumer and trader-reported maize sourcing, sales, and purchase behavior. Finally, we assess whether the effects of the intervention varied by framing (i.e., presenting the information in terms of the risks of consuming maize contaminated with aflatoxin or the benefits of consuming aflatoxin-safe maize).

5.1. Effect of intervention on maize quality

Table 6.4 presents regression results on the effect of the intervention on maize quality. Columns 1 and 2 report OLS estimates of the intervention's impact on the proportion of damaged kernels in a 100-gram maize sample sold by traders at the time of visit. Column 3 reports results from a linear probability model using a categorical quality indicator: whether the sample had more than 10% damaged kernels (low quality). Panel A presents results from the first follow-up, while Panel B reports results from the second follow-up.

Column (1) shows that the intervention had no significant effect on the proportion of damaged kernels at follow-up 1. However, column (2), which uses the log-transformed proportion, indicates a statistically significant reduction of 0.147 log points ($p < 0.05$), equivalent to about a 15% decline in damaged kernels relative to control market samples. Results from the quality dummy variable indicate that, at the first follow-up, the intervention reduced the likelihood of maize being of low quality by 11 percentage points.

Next, we turn to Panel B, which presents results from the second follow-up. In both control and treatment markets, maize quality improved over this period relative to the first follow-up: the share of poor-quality maize declined from 46% to 30% in control markets, likely reflecting seasonal improvements as fresh harvests entered the markets. Together, these results suggest that the quality improvements observed at the first follow-up were short-lived and dissipated as market turnover and seasonal supply changes dominated, consistent with prior evidence on the limited persistence of information-based interventions (Bailey et al., 2020; Hoffmann, Moser, et al., 2021).

Treatment effects at the second follow-up could, in principle, be attenuated by spillovers from treated to nearby control markets. Markets in the study area are geographically proximate: the average minimum distance to the nearest neighboring market is approximately 3.2 km, with half of markets located within about 2.6 km of another market. To account for potential spatial spillovers, we re-estimate the main specifications including measures of exposure to nearby treated markets and an indicator for markets with no neighboring markets within a given radius, following Hoffmann et al. (2022). Results are presented in Appendix Table 6.3. The treatment effects observed at the first follow-up remain robust and are, if anything, slightly larger in magnitude—particularly when using 4 km and 6 km exposure radii. While coefficients capturing exposure to nearby treated markets among control markets are occasionally negative, they are generally small and imprecisely estimated. Importantly, results at the second follow-up remain statistically insignificant across specifications, implying minimal spillovers in this season.

Table 6.4: Effect of information on the quality of maize

	1	2	3
	Proportion of damaged kernels	Proportion of damaged kernels (log)	Above 10% damaged (dummy)
Panel A: Follow-up 1			
Treatment	-0.010	-0.147**	-0.110**
	(0.009)	(0.070)	(0.046)
Observations	587	584	587
Mean of control of group	0.115	-2.419	0.464
Panel B: Follow-up 2			
Treatment	0.001	0.034	0.015
	(0.009)	(0.074)	(0.046)
Observations	531	530[a]	531
Mean of control group	0.097	-2.596	0.304

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Standard errors clustered at trader level in parentheses. All regressions include both trader and market control variables. Trader controls include sex, age, education level, years of experience in the maize business, and an indicator for whether the trader was interviewed at baseline. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market. [a] One observation was dropped in column 2 due to a zero value.

5.2. Effect of intervention on maize prices

One might expect that an improvement in maize quality during follow-up 1 would translate into a change in prices in treatment markets. To test this, we examine the effect of the intervention on average maize prices, measured as the trader-reported price per kilogram of the maize sample at the time of interview. Table 6.5 presents the results for follow-up 1[39]. Column (1) shows that the treatment effect on price is negative and statistically significant. However, the magnitude of the effect is modest relative to the mean price among control traders, corresponding to only a 2 percent decrease.

[39] We limit this analysis to follow-up 1 because there was no quality improvement at follow-up 2.

The treatment effect on price was likely to depend on the quality levels. For example, the intervention could have reduced prices for lower-quality maize if consumers became more discerning. To assess this, we include interaction terms between treatment and maize quality measures (columns 2 and 3 of Table 5). The interaction coefficients are not statistically significant, indicating that lower-quality maize did not attract a substantial price penalty. Nonetheless, the negative interaction terms—particularly in Column (3)—suggest that treated traders selling maize with more than 10 percent damage may face slightly larger price discounts relative to good-quality maize. Overall, the lack of statistical significance provides limited evidence that the intervention induced systematic price differentiation based on quality.

Table 6.5: Effect of the intervention on maize prices (Follow-up 1)

	(1)	(2)	(3)
	Price per kg (Kes/kg)	Price per kg (Kes/kg)	Price per kg (Kes/kg)
Treatment	-1.648**	-1.724	-1.309
	(0.800)	(2.211)	(1.269)
Proportion damaged (log)		5.709	
		(4.293)	
Treatment * proportion damaged (log)		-0.030	
		(0.813)	
Above 10% damaged			1.172
			(1.735)
Treatment * Above 10% damaged			-0.565
			(2.082)
Observations	571	569	571
R-squared	0.174	0.177	0.175
Mean of the control	75.539	75.539	75.539
Combined effect		-1.755	-1.874
SE of the combined effect		2.983	1.385

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Standard errors clustered at trader level in parentheses. Columns (1) estimate the effect of the intervention on maize price in KES per kilo. Columns (3) and (4) include interaction terms between treatment and the two quality measures to assess whether the intervention modified the relationship between quality and price. All regressions include both trader and market control variables. Trader controls include sex, age, education level, years of experience in the maize business, and an indicator for whether the trader was interviewed at baseline. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market.

5.3. Effect of intervention on sales volumes

Columns (1) and (2) of Table 6.6 report the impact of the treatment on the total volume of maize sold during the last three days at the first follow-up, using two alternative dependent variables:

sales volume in kilograms[40] and its inverse hyperbolic sine (IHS) transformation[41]. Column (1) indicates a statistically significant negative effect of approximately five kilograms on average, corresponding to a 21 percent decrease relative to the control group. Consistent with this result, applying the IHS transformation to account for skewness shows that the intervention is associated with a statistically significant reduction in maize sales among treated traders. To assess whether the observed reduction in maize sales was driven by quality considerations, we include interaction terms between the treatment and two measures of maize quality in columns (3) and (4) of Table 6.6. Column (3) shows that the intervention significantly reduced overall maize sales volumes. However, the effect was more pronounced for maize with higher proportions of damaged kernels, as indicated by the negative and weakly significant interaction term (–0.328, $p < 0.10$). In Column (4), the intervention had no significant effect on sales volumes of good-quality maize (≤10% broken kernels). In control markets, poor-quality maize (>10% broken) sold in slightly larger volumes than good-quality maize, but this difference was not statistically significant. In treatment markets, however, sales of poor-quality maize declined significantly; the interaction coefficient of –0.607 ($p < 0.05$) indicates a substantial reduction in sales volumes for maize with more than 10% broken kernels. These results suggest that the information campaign made consumers more sensitive to visible quality deterioration, leading to larger sales declines for poorer-quality maize.

We complement this analysis by using the amount of maize sold on the previous market day as an alternative measure of sales volumes. The results, presented in Appendix Table 6.3, are

[40] Winsorized at the 0 and 95th percentiles by treatment status to reduce the influence of extreme values.
[41] We acknowledge the limitations of using the IHS transformation, particularly with respect to interpretation in terms of percentage changes (de Brauw & Herskowitz, 2021). For this reason, we use the variable measured in kilograms when interpreting magnitude, while the IHS-transformed variable is used as a robustness check against the influence of extreme values in the kilogram measure.

largely similar, except for the interaction terms between the continuous measure of quality and treatment, which lose statistical significance.

Table 6.6. Effect of intervention on sales volume (Follow up 1)

	(1)	(2)	(3)	(4)
	Amount sold (kg)	Amount sold (IHS)	Amount Sold (IHS)	Amount sold (IHS)
Treatment	-8.104**	-0.363***	-0.954**	0.112
	(3.136)	(0.135)	(0.464)	(0.176)
Proportion of damaged kernels (log)			0.015	
			(0.110)	
Treatment * proportion damaged			-0.328*	
			(0.176)	
Above 10% broken				0.089
				(0.176)
Treatment * Above 10%				-0.607**
				(0.284)
Observations	642	642	522	523
R-squared	0.221	0.153	0.200	0.199
Mean of the control	38.569	3.285	3.285	3.285

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Standard errors clustered at the market level in parentheses. Columns (1) and (2) estimate the effect of the intervention on sales volume, presented as an IHS transformation of the sales volumes. Columns (3) and (4) include interaction terms between treatment and the respective quality measures to assess whether the intervention modified the relationship between quality and sales volume. All regressions include both trader and market control variables. Trader controls include sex, age, education level, years of experience in the maize business, and an indicator for whether the trader was interviewed at baseline. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market.

5.4. Channels of impact

5.4.1. Effect on consumer level outcomes

Table 6.7 reports the effects of the intervention on consumer-reported outcomes: (i) whether the consumer had ever heard of aflatoxins, (ii) whether the consumer knew at least one health effect of aflatoxin exposure, (iii) awareness of the link between kernel integrity and aflatoxin contamination, and (iv) whether the consumer reported checking kernel integrity when purchasing maize.

The results show modest but statistically insignificant effects of the intervention on aflatoxin awareness, possibly due to the already high level of awareness of aflatoxin in the region. However, consumers in treatment markets were approximately 30 percent more likely to recognize the link between kernel integrity and aflatoxin contamination than consumers in control markets, although this effect was not statistically significant. By contrast, the intervention significantly increased the likelihood that consumers checked kernel integrity when purchasing maize, with consumers in treatment markets being 19 percentage points (a 56 percent increase relative to the control group) more likely to do so.

Table 6.7. Effect of information on consumer-level outcomes

	(1)	(2)	(3)	(4)
	Ever heard of aflatoxin	Knows at least one health effect of exposure to aflatoxins	Knows about the correlation between kernel integrity and aflatoxin contamination	Considers kernel integrity while purchasing maize
Treatment	0.064	0.009	0.027	0.185***
	(0.057)	(0.058)	(0.046)	(0.070)
Observations	187	187	187	187
Mean of the control	0.81	0.71	0.066	0.33

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Standard errors, clustered at the market level in parentheses. Control variables include both consumer and market variables. Consumer-level controls include sex, age, and education level. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market.

5.4.2. Effect of the intervention on trader behavior

Table 6.8 shows that the information campaign influenced trader behavior related to sourcing and quality management as reported during the first follow-up. The treatment significantly increased the likelihood that traders reported checking for kernel integrity (Column 1) when sourcing maize, a key visual cue emphasized in the campaign. Column 2 presents the results on whether the trader was observed sorting maize at the time of the surveys by the enumerator. While observed sorting (Column 2) did not increase significantly, the estimated 5-percentage point rise—equivalent to a 21 percent increase relative to the control—suggests a potentially meaningful behavioral shift. When asked about the reason for sorting, a few traders mentioned the removal of the damaged kernels. The proportion that mentioned the removal of broken kernels was four times higher in the treatment than in the control markets.

Taken together, these trader-reported outcomes are consistent with the short-run quality improvements observed at the first follow-up in Table 4. While traders appear to have adjusted their sourcing or sorting behavior in response to the intervention, these changes did not translate into greater maize price differentiation across quality grades (Column 4 of Table 6.8), in line with the results in Table 6.5, which show no evidence of price premia for higher-quality maize. This pattern suggests that traders faced limited incentives to segment the market based on quality. Instead, as shown in Table 6.6, the primary market adjustment occurred through quantities rather than prices, with quality improvements associated with larger reductions in sales of lower-quality maize.

Table 6.7. Effect of the intervention on trader behavior related to sourcing and quality management

	(1)	(2)	(3)	(4)
	Trader reports that they check for kernel integrity	Observed sorting at follow-up	Trader removes broken kernels when sorting (trader reported)	Trader had more than one maize type at the time of visit
Treatment	0.262***	0.047	0.026***	-0.033*
	(0.037)	(0.045)	(0.009)	(0.020)
Observations	642	642	642	642
R-squared	0.122	0.109	0.050	0.098
Mean of the control	0.242	0.261	0.006	0.125

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Standard errors in parentheses. All regressions include both trader and market control variables. Trader controls include sex, age, education level, years of experience in the maize business, and an indicator for whether the trader was interviewed at baseline. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market.

5.5. Longer-Term Effects

Table 6.9 presents trader (including sales volume)- and consumer-level outcomes at the second follow-up. Relative to the first follow-up (Table 6.8), the trader level treatment effects appear weaker and less consistent. Specifically, the intervention continued to increase self-reported checking for kernel integrity by 22 percentage points, similar in magnitude to follow-up 1. However, no significant effects were observed for sorting practices or removal of broken kernels. In addition, the decline in sales volumes observed at the earlier follow-up attenuates in magnitude in Columns (5 and 6) of Table 6.9, suggesting that these effects were short-lived.

At the consumer level, modest but significant effects remain: treatment raised the likelihood of having heard of aflatoxins by nine percentage points and of considering kernel integrity when purchasing maize by eight percentage points. While the effects on knowledge of health risks are small and not statistically significant, knowledge of the link between kernel integrity and aflatoxin contamination is large and statistically significant. These patterns suggest that while some consumer awareness and self-reported trader practices persisted, behavioral adjustments in sorting evident at follow-up 1 did not carry through to follow-up 2.

Table 6.9. Effect of the intervention on trader outcomes and consumer behavior at follow-up 2

	(1)	(2)	(3)	(4)	(5)	6
P*anel A: Effect of information on trader reported outcomes at follow-up 2*						
	Trader reports that they check for kernel integrity	Observed sorting at follow-up	Trader removes broken kernels when sorting (trader reported)	Trader had more than one maize type at the time of visit	Amount sold (IHS)	Amount sold (Kg)
Treatment	0.216***	0.001	0.002	-0.012	-0.114	-6.018*
	(0.038)	(0.035)	(0.015)	(0.016)	(0.179)	(3.392)
Observations	636	636	636	636	636	636
Mean of the control	0.130	0.099	0.121	0.088	2.726	0.218
Panel B: Effects on consumer outcomes at follow-up 2						
	Ever heard of aflatoxin	Knows at least one health effect of exposure to aflatoxins	Knows about the correlation between kernel integrity and aflatoxin contamination	Considers kernel integrity while purchasing maize		
Treatment	0.093**	0.068	0.107**	0.079*		
	(0.037)	(0.047)	(0.042)	(0.040)		
Observations	265	265	265	265		
Mean of the control	.854	.769	.215	.408		

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Standard errors, clustered at the market level in parentheses. Control variables include both trader and market variables. Trader controls include sex, age, education level, years of experience in the maize business, and an indicator for whether the trader was interviewed at baseline. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market.

5.6. Effects of information framing (negative versus positive framing)

5.6.1. Effects of framing on quality outcomes

The improvement in quality observed during follow-up 1 appears to be driven by the positive frame of the intervention (Table 6.10). The positive frame of the intervention significantly reduced the proportion of damaged kernels and its log transformation, and the coefficient equivalence tests confirm that these effects are statistically stronger than those of negative framing ($p = 0.020$ and $p = 0.021$, respectively). By contrast, although positive framing significantly reduced the likelihood of >10% damage, these effects were not statistically different from those under negative framing ($p = 0.481$).

Our results generally suggest that positive framing was more effective than negative framing in improving maize quality (safety). ThiGallagher & Updegraff (2012)as Gallagher & Updegraff (2012) and O'Keefe & Jensen (2007), which show that gain frames are generally more persuasive than loss frames. The mechanisms driving quality improvement in our case depend on both trader and consumer behavior. Since these groups may have different objectives, they are likely to internalize the advocated behavior differently and thus effects might vary between them (Rothman et al., 1997). To enhance our understanding, we examine the effect of framing on both trader and consumer behavior in the next sections.

Table 6.10. Effect of information framing on the quality of maize

	(1)	(2)	(3)
	Proportion of damaged kernels	Proportion damaged (log)	Above 10% damaged
Positive framing	-0.023***	-0.248***	-0.127**
	(0.009)	(0.084)	(0.053)
Negative framing	0.010	0.000	-0.082
	(0.014)	(0.090)	(0.059)
Observations	587	584	587
R-squared	0.062	0.092	0.092
Mean of the control	0.115	-2.419	0.464
TP=TN (P value)	0.020	0.021	0.481

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Standard errors clustered at trader level in parenthesis. All regressions include both trader and market control variables. Trader controls include sex, age, education level, years of experience in the maize business, and an indicator for whether the trader was interviewed at baseline. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market.

5.6.2. Effect of framing on trader and consumer outcomes

Results for trader-level reported behavior show differential responses by framing, consistent with the quality improvements observed at the first follow-up (Table 6.11). Positive framing significantly increased self-reported checking of maize quality (by 23.2 percentage points, $p < 0.01$) and led to observable quality-improving behavior, as evidenced by an increase in reported removal of broken kernels (by 3.5 percentage points, $p < 0.05$). Positive framing also reduced the likelihood that traders stocked more than one maize type (by 4.9 percentage points, $p < 0.05$), suggesting a narrowing of product offerings consistent with short-run quality management. In contrast, while negative framing substantially increased self-reported checking of maize quality (by 30.1 percentage points, $p < 0.01$), it did not translate into significant changes in observable sorting behavior or product offerings. Although coefficient equivalence tests indicate no statistically significant differences between the two framings across outcomes, the pattern of

results suggests that positive framing was more likely to induce tangible, short-run quality adjustments by traders, aligning with the stronger effects of positive framing on continuous quality measures documented earlier.

Table 6.11. Effect of positive and negative frames on trader-level outcomes

	(1)	(2)	(4)	(6)
	Trader reports that they check for kernel integrity	Observed sorting at follow-up	Trader removes broken Kernels	Trader had more than one maize type
Positive framing (TP)	0.232***	0.066	0.035***	-0.049**
	(0.043)	(0.055)	(0.013)	(0.020)
Negative framing (TN)	0.301***	0.024	0.015	-0.012
	(0.050)	(0.056)	(0.010)	(0.031)
Observations	642	642	642	642
R-squared	0.124	0.110	0.053	0.099
Mean of the control	0.242	0.261	0.006	0.125
TP=TN (P value)	0.205	0.526	0.211	0.246

Notes: Significance: *** = $p < 0.01$; ** = $p < 0.05$; * = $p < 0.1$. Standard errors, clustered at the market level in parentheses. Control variables include both trader and market variables. Trader controls include sex, age, education level, years of experience in the maize business, and an indicator for whether the trader was interviewed at baseline. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market.

At the consumer level, framing effects on aflatoxin awareness and knowledge were generally imprecisely estimated (Table 6.13). While consumers in negatively framed markets exhibited larger point estimates for knowledge-related outcomes—such as awareness of the correlation between kernel integrity and aflatoxin—these differences are not statistically significant. By contrast, both framings significantly increased the likelihood that consumers reported considering kernel integrity when purchasing maize, by 18 percentage points under positive framing ($p < 0.05$) and 20 percentage points under negative framing ($p < 0.05$), with no

statistically significant difference between treatments. Together, these results suggest that negative framing increased the salience of the risk of aflatoxin more for consumers, whereas positive framing was more effective in eliciting observable quality-related responses among traders. This asymmetry is consistent with an avoidance-based mechanism, whereby consumer concern—particularly under negative framing—reduces demand for visibly poor-quality maize, while positive framing encourages traders to make marginal, low-cost quality adjustments without generating sustained price premia. The results align with studies that present loss-frames as more effective, especially in health messaging (Balew et al., 2025), and productivity enhancing (Ferraro & Tracy, 2022).

Table 6.13. Effect of positive and negative framing on consumer-level outcomes

	(1)	(5)	(7)	(9)
	Ever heard of aflatoxin	Knows at least one health effect of exposure to aflatoxins	Knows the correlation between kernel integrity and aflatoxin	Considers kernel integrity while purchasing
Positive framing	0.027	-0.034	-0.020	0.175**
	(0.061)	(0.077)	(0.054)	(0.085)
Negative framing	0.102	0.054	0.077	0.195**
	(0.073)	(0.068)	(0.060)	(0.089)
Observations	187	187	187	187
R-squared	0.169	0.163	0.191	0.242
Mean of the control	0.813	0.714	0.066	0.330
T1=T2 (P-value)	0.293	0.321	0.158	0.844

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Standard errors, clustered at the market level in parentheses. Control variables include both trader and market variables. Trader controls include sex, age, education level, years of experience in the maize business, and an indicator for whether the trader was interviewed at baseline. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market.

6. Discussion and conclusion

This study used a randomized controlled trial (RCT) to test whether providing both traders and consumers with information on the correlation between kernel integrity and aflatoxin contamination in maize could stimulate demand for, and supply of, higher-quality—and by extension safer—maize in informal markets. In the short term, we find modest improvements in maize quality in treatment markets, driven by behavioral changes among traders (e.g., removing broken kernels, checking quality during sourcing) and by consumers paying greater attention to kernel integrity at purchase. However, we find no evidence that high-quality maize fetched a price

premium. Instead, overall sales volumes declined, largely due to reduced sales of low-quality maize in treatment markets, suggesting that consumers avoided visibly poor-quality maize.

Several factors may explain why the quality improvements observed at the first follow-up did not translate into price premiums. First, the magnitude of improvement may have been too small for consumers to clearly perceive or value as worth paying more for. Second, many consumers—who are also smallholder farmers—may be reluctant to pay higher prices for quality maize when they typically sell at low prices and buy at high prices (Burke et al., 2019). This reflects broader dynamics in Kenya's informal maize markets, where farmers rarely receive premiums for higher-quality grain (Abate et al., 2021; Bergquist & Dinerstein, 2020). Third, the absence of organized actors such as millers or farmer cooperatives—who in other contexts help transmit rewards for unobservable quality attributes (Do Nascimento Miguel, 2024)—limits the potential for premiums to emerge. Most traders in our sample sourced maize from other traders, introducing additional intermediaries and making it harder for incentives to reach upstream suppliers. Future research should examine the conditions under which price premiums for quality can emerge in such contexts. The absence of price premiums in our study underscores that information alone is unlikely to sustain higher quality and incentives along the value chains; complementary mechanisms that strengthen incentives along the value chain will be required.

The decline in maize sales volumes in treatment markets is consistent with patterns observed in other commodities (see for example Lin et al., 2024). However, it is unclear whether this reflects traders sorting and diverting low-quality maize to other uses (e.g., livestock feed), consumers reducing purchases by substituting maize with other foods, or consumers sourcing from trusted alternatives such as neighbors. Further research is needed to better understand the

mechanisms driving the reduction in sales volumes, particularly the welfare and nutrition implications if food safety concerns lead consumers to reduce intake of specific foods.

While not conclusive, our study suggests that positive framing (gain-frame) was more effective in improving maize quality and stimulating quality-enhancing behavior among traders, whereas negative framing (loss-frame) appeared more persuasive among consumers. The stronger effect of positive framing on traders may reflect their profit motivation: since they know consumers value the health benefits of maize without broken kernels, gain-framed messages are more persuasive because compliance can translate into higher sales or customer retention. For consumers, however, the relevant outcome is health, and framing can operate differently depending on how risks are perceived (e.g., observability and frequency of consequences) and how the mitigating behavior is linked to the risk (Rothman et al., 1997). If consumers believe they have already suffered health damage from contaminated maize, they may see little benefit from switching to safer maize—making loss framing less persuasive. Conversely, if they believe health effects can be reversed, loss framing may be more compelling (see for example Balew et al., 2025). This aligns with Szaszi et al. (2022), who note that framing effectiveness is highly context dependent. Further research is needed to better understand how framing influences different market actors and how these insights can be leveraged to increase the effectiveness of information interventions.

Lastly, although trader and consumer self-reported behaviors persisted beyond the first follow-up, we find no lasting improvements in maize quality at the second follow-up. This pattern suggests that the observed effects may reflect a novelty response to new information that attenuated over time, or that behavioral changes require continued reinforcement to translate into sustained quality improvements. An alternative explanation is that seasonal dynamics—such as the influx of

fresh harvests that improved quality across all markets—may have masked treatment effects in the longer run. These findings are consistent with prior evidence that information-based interventions often generate short-lived impacts unless complemented by ongoing engagement or incentives (Bailey et al., 2020; Hoffmann, Moser, et al., 2021).

The absence of long-term effects underscores the limits of information alone: durable improvements in food safety in informal markets likely require repeated campaigns, complementary interventions, or institutional mechanisms that sustain incentives for quality upgrading. Overall, our results highlight both the promise and the constraints of information-led approaches in settings with weak formal regulation. While simple, observable food safety information can generate modest, short-term improvements in maize quality—and may be applicable to other foods where safety correlates with visual cues—the lack of price premiums for higher-quality maize suggests that information alone is unlikely to sustain quality upgrading.

Our study is not without limitations. Beyond the relatively short duration of the intervention, we did not directly test for aflatoxin contamination using laboratory analysis, which is costly and time intensive. Emerging applications of artificial intelligence and machine learning offer promising opportunities to reduce the cost of quality monitoring and enforcement in food systems in low-income countries (Chakraborty et al., 2021; Gachoki et al., 2025). Future research should examine how these technologies can complement information-based interventions to enable scalable and sustained improvements in food safety.

Appendix 6

Appendix Table 6.1. Balance checks of the analysis sample (Follow-up 1)

	Control (N=360)		Treatment (N=282)		Positive frame (N=153)		Negative frame (N=129)					
	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	P value (5-2)	P value (8-2)	P value (11-2)	P value (11-8)
Age of the retailer in years	42.0	12.0	41.0	12.3	40.6	11.7	41.5	13.0	0.425	0.362	0.965	0.656
Age of the retailer (missing)	0.1	0.2	0.0	0.2	0.0	0.2	0.0	0.2	0.425	0.424	0.823	0.736
Retailer is male	0.2	0.4	0.2	0.4	0.2	0.4	0.2	0.4	0.528	0.522	0.856	0.776
Retailer had primary level education or above	0.8	0.4	0.8	0.4	0.8	0.4	0.8	0.4	0.193	0.623	0.164	0.624
Years in maize retail business	8.2	8.1	6.6	7.2	7.1	7.5	5.9	6.9	**0.038**	0.595	0.028	0.287
Years in maize retail business (missing)	0.0	0.1	0.0	0.1	0.0	0.1	0.0	0.0	0.143	0.630	0.015	0.285
Share of pen air retailers	0.1	1.8	0.3	0.3	0.3	0.3	0.2	0.2	0.579	0.341	0.993	0.116
Total number of traders	17.2	14.4	12.2	8.1	14.0	9.5	10.0	5.3	0.179	0.714	**0.026**	0.127
Total amount sold in the previous market day in a given market	171.9	139.6	117.0	87.4	120.2	90.6	113.1	83.7	0.107	0.276	0.176	0.830
Average proportion of damaged kernels per sample in a given market	0.1	0.0	0.1	0.0	0.1	0.1	0.1	0.0	0.386	0.600	0.577	0.974

Average price per kg in a given market	73.1	6.1	73.5	5.6	73.5	4.8	73.4	6.4	0.781	0.780	0.928	0.927
Trader interviewed at baseline	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.845	0.875	0.669	0.718

Appendix Table 6.2. Balance checks of the analysis sample (Follow-up 1)

	Control (N=348)			Treatment (N=288)			Positive frame (N=150)			Negative frame (N=138)						
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Variable		Mean	SD		Mean	SD		Mean	SD		Mean	SD	P value (5-2)	P value (8-2)	P value (1-2)	P value (11-8)
Age of the retailer in years		41.9	11.7		42.0	12.3		41.3	12.0		42.8	12.6	0.937	0.586	0.559	0.498
Age of the retailer (missing)		0.1	0.2		0.1	0.2		0.1	0.2		0.0	0.2	0.766	0.769	0.424	0.509
Retailer is male		0.2	0.4		0.1	0.4		0.1	0.4		0.2	0.4	0.476	0.577	0.710	0.906
Retailer had primary level education or above		0.8	0.4		0.8	0.4		0.8	0.4		0.9	0.4	0.383	0.823	0.071	0.283
Years in maize retail business		8.0	7.9		6.7	7.5		7.0	7.6		6.3	7.4	0.126	0.646	0.129	0.557
Years in maize retail business (missing)		0.0	0.1		0.0	0.1		0.0	0.1		0.0	0.0	0.419	0.720	0.011	0.162
Share of pen air retailers		0.0	1.9		0.3	0.3		0.3	0.3		0.2	0.2	0.506	0.335	0.778	0.190
Total number of traders		16.4	14.0		12.0	7.9		13.7	9.5		10.1	5.1	0.219	0.794	**0.040**	0.166
Total amount sold in the previous market day in a given market		169.7	133.9		121.5	88.0		120.7	90.7		122.3	85.4	0.128	0.255	0.304	0.962
Average proportion of damaged kernels per sample in a given market		0.1	0.0		0.1	0.0		0.1	0.1		0.1	0.0	0.454	0.462	0.833	0.780

Average price per kg in a given market	73.0	6.1	73.3	5.8	73.7	4.9	73.0	6.6	0.789	0.593	0.892	0.700
Trader interviewed at baseline	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.5	0.469	0.980	0.336	0.582

Appendix Table 6.3. Effect of Information on Maize Quality, Accounting for Potential Spillovers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Proportion of broken kernels	Proportion of broken kernels	Proportion of broken kernels	Proportion damaged (log)	Proportion damaged (log)	Proportion damaged (log)	Above 10% damaged	Above 10% damaged	Above 10% damaged
Distance in KM	3 KM	4 KM	6 KM	3 KM	4 KM	6 KM	3 KM	4 KM	6 KM
Panel A: Follow-up 1									
Treatment	-0.013	-0.028**	-0.030**	-0.088	-0.251**	-0.491***	-0.074	-0.145**	-0.124
	(0.009)	(0.011)	(0.015)	(0.091)	(0.101)	(0.167)	(0.062)	(0.069)	(0.100)
Share treated within X km * treatment	0.023	0.041	0.051**	-0.024	0.234	0.660**	-0.037	0.096	0.039
	(0.027)	(0.028)	(0.023)	(0.171)	(0.172)	(0.263)	(0.108)	(0.112)	(0.168)
Share treated within X km * control	0.011	-0.013	0.005	0.175	-0.083	-0.071	0.043	-0.006	-0.007
	(0.020)	(0.016)	(0.019)	(0.150)	(0.132)	(0.166)	(0.107)	(0.094)	(0.118)
Observations	587	587	587	584	584	584	587	587	587
R-squared	0.055	0.064	0.062	0.080	0.084	0.096	0.091	0.090	0.092
Mean of the control	0.115	0.115	0.115	-2.419	-2.419	-2.419	0.464	0.464	0.464
Panel B: Follow-up 2									
Treatment	-0.005	0.002	0.010	-0.039	0.025	0.048	-0.004	0.011	-0.039
	(0.013)	(0.016)	(0.019)	(0.098)	(0.114)	(0.154)	(0.066)	(0.075)	(0.102)
Share treated within X km * treatment	0.007	0.011	-0.002	0.213	0.165	0.079	0.030	0.132	0.141
	(0.026)	(0.028)	(0.026)	(0.182)	(0.187)	(0.260)	(0.112)	(0.120)	(0.169)

Share treated within X km * control	-0.006	0.017	0.015	0.030	0.128	0.085	0.002	0.100	0.016
	(0.026)	(0.023)	(0.021)	(0.190)	(0.160)	(0.171)	(0.120)	(0.098)	(0.114)
Observations	531	531	531	530	530	530	531	531	531
R-squared	0.077	0.078	0.078	0.094	0.093	0.092	0.080	0.084	0.082
Mean of the control	0.097	0.097	0.097	-2.596	-2.596	-2.596	0.304	0.304	0.304

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Standard errors clustered at trader level in parentheses. All regressions include both trader and market control variables. Trader controls include sex, age, education level, years of experience in the maize business, and an indicator for whether the trader was interviewed at baseline. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market. Spillover exposure is measured as the share of neighboring markets assigned to treatment within a given radius (3 km, 4 km, or 6 km). For each distance, this share is interacted separately with the treatment and control indicators to allow spillover effects to differ between treated and control markets. All specifications also include an indicator for markets with no neighboring markets within the specified radius.

Appendix Table 6.4. Effect of intervention on sales volume during the previous market day

	(1)	(2)	(3)	(4)
	Amount sold previous market day (kg)	Amount sold previous market day (IHS)	Amount sold market day (IHS)	Amount sold market day (IHS)
Treatment	-9.865	-0.525***	-0.644	-0.154
	(6.948)	(0.184)	(0.613)	(0.210)
Proportion of damaged kernels (log)			-0.006	
			(0.137)	
Treatment * proportion damaged			-0.114	
			(0.218)	
Above 10% broken				0.113
				(0.230)
Treatment * Above 10%				-0.504*
				(0.292)
Constant	179.698	6.489***	7.111***	7.093***
	(119.169)	(1.123)	(1.292)	(1.240)
Observations	642	642	522	523
R-squared	0.124	0.215	0.231	0.235
Mean of the control	36.400	2.502	2.502	2.502

Notes: Significance: *** = p < 0.01; ** = p < 0.05; * = p < 0.1. Standard errors clustered at the market level in parentheses. Columns (1) and (2) estimate the effect of the intervention on sales volume during the previous market day, presented as an IHS transformation of the sales volumes. Columns (3) and (4) include interaction terms between treatment and the respective quality measures to assess whether the intervention modified the relationship between quality and sales volume. All regressions include both trader and market control variables. Trader controls include sex, age, education level, years of experience in the maize business, and an indicator for whether the trader was interviewed at baseline. Market controls include the average quality of maize samples collected at baseline, the average maize price at baseline, total maize sales volume at baseline, the proportion of open-air kiosks in the market, and the number of traders in the market.

Appendix 6.2: Information Scripts

Treatment 1: Positive framing

Once you get to the market, identify all the traders in the market and provide them with the following information:

My name is XXXX. I work with the University of Nairobi. We have some important information for you, concerning aflatoxin contamination. Aflatoxin is a poison produced by certain types of fungus that live in the soil and on dead decaying matter. Aflatoxin affects many crops, especially maize. While it is not possible to see whether maize grains are safe from aflatoxin contamination from the outside, there are some observable characteristics that one can use to identify safer maize.

Research found that maize with few broken grains is safer from aflatoxins compared to maize with many broken grains

I am going to leave you with some flyers, please be sure to pass them out to all consumers purchasing maize from your shop.

PURCHASE MAIZE WITH NO BROKEN GRAINS TO INCREASE CHANCES OF THE MAIZE BEING SAFE FROM AFLATOXIN CONTAMINATION.

After speaking with the traders, identify the main entrances to the market. Intercept ALL the consumers coming into and leaving the market. Provide the following information plus a flyer.

My name is XXXX. I work with the University of Nairobi. We have some important information for you, concerning aflatoxin contamination. Aflatoxin is a poison produced by certain types of fungus that live in the soil and on dead decaying matter. Aflatoxin affects many crops, especially maize and groundnut.
There are several benefits of consuming aflatoxin safe foods:

i. It reduces your chances of getting liver cancer
ii. Your children stay safe from stunting

While it is not possible to see whether maize grains are safe from aflatoxin contamination from the outside, there are some observable characteristics that one can use to identify safer maize. Research found that maize with few broken grains is safer from aflatoxins compared to maize with many broken grains

PURCHASE MAIZE WITH NO BROKEN GRAINS TO INCREASE CHANCES OF THE MAIZE BEING SAFE FROM AFLATOXIN CONTAMINATION.

Treatment 2: Negative framing

Once you get to the market, identify all the traders in the market and provide them with the following information:

My name is XXXX. I work with the University of Nairobi. We have some important information for you, concerning aflatoxin contamination. Aflatoxin is a poison produced by certain types of fungus that live in the soil and on dead decaying matter. Aflatoxin affects many crops, especially maize. While it is not possible to see whether maize grains are safe from aflatoxin contamination from the outside, there are some observable characteristics that one can use to identify safer maize.

Previous research has shown that maize with more broken grains is likely to be more contaminated compared to maize with few broken grains.

I am going to leave you with some flyers, please be sure to pass them out to all consumers purchasing maize from your shop.

AVOID MAIZE WITH BROKEN GRAINS TO REDUCE CHANCES OF EXPOSURE TO AFLATOXIN

After speaking with the traders, identify the main entrances to the market. Intercept ALL the consumers coming into and leaving the market. Provide the following information plus a flyer.

My name is XXXX. I work with the University of Nairobi. We have some important information for you, concerning aflatoxin contamination. Aflatoxin is a poison produced by certain types of fungus that live in the soil and on dead decaying matter. Aflatoxin affects many crops, especially maize and groundnut.
Aflatoxin is harmful and affects human health when consumed. Below are some of the health effects associated with the consumption of contaminated foods:

i. It increases the risk of liver cancer
ii. Is suspected of causing stunting in young children

While it is not possible to see whether maize grains are safe from aflatoxin contamination from the outside, there are some observable characteristics that one can use to identify safer maize.

A study has shown that maize with more broken grains is likely to be more contaminated compared to maize with few broken grains. In that study, maize with at least 1 broken grains in every 10 grains contained about twice as much aflatoxin level as maize without any broken kernels.

AVOID MAIZE WITH BROKEN GRAINS TO REDUCE CHANCES OF EXPOSURE TO AFLATOXIN

Appendix 6.3: Information flyers/posters



Chapter 7

Synthesis

7.1. Introduction

Evidence from decades of research on small-scale agriculture and economic transformation in low-income countries shows that the adoption of innovations by small-scale farmers is crucial for driving structural change in these economies (Gollin et al., 2021). Yet, despite the availability of modern, productivity-enhancing technologies, adoption rates remain low, resulting in the persistent large productivity gap observed in these countries (Dar et al., 2020; Suri & Udry, 2022). The literature highlights that there is no single binding constraint limiting adoption but rather multiple factors including risk, information, imperfect input and output markets, credit and liquidity limitations, high transaction costs, weak infrastructure, and imperfections in labor and land markets (Bridle et al., 2020; Macours, 2019; Suri & Udry, 2022). A growing body of research has sought to better understand the adoption puzzle and to address barriers to uptake, however, important gaps remain on understanding the adoption process. This thesis contributes to that literature. The overarching objective is to examine how risk perceptions, technology attributes and perceptions of them, information, and dynamics in informal markets shape the adoption (process) of agricultural innovations.

The thesis is guided by a theory of change that places the adoption of productivity-enhancing technologies by small-scale farmers at the center of economic transformation, characterized by rising productivity and a gradual decline in the share of households engaged in subsistence production. Adoption is conceptualized as a process shaped by farmers' assessment of the risks they face or their needs when it comes to agricultural production, their awareness of

available technologies (influenced by access to information), and their experience with these technologies. Specifically, the thesis examines how agricultural risks and farmers' perceptions of these risks (including both their type and attributes), technology attributes, information (learning modalities and framing), demand and supply-side dynamics for safe food in informal markets influence technology adoption among small-scale farmers and market outcomes. The five chapters draw on both experimental and non-experimental methods and rely on a diverse sample of participants, including farmers, consumers, and traders.

What follows is a discussion of the key lessons and insights from the findings and their implications for technology adoption among small-scale farmers, as well as for policy and future research.

7.2. Key lessons and insights

7.2.1. Salience of multiple risks, heterogeneity in farmer perceptions, and technology adoption

The adopter–perception paradigm of technology adoption emphasizes the role of farmers' perceptions of their needs and of the "relevant" attributes of a technology (Ruzzante et al., 2021). In essence, adoption depends on whether farmers perceive a technology as beneficial given their needs and risk context. Prior work has linked risk perceptions and preferences to technology adoption (Feyisa et al., 2023), and understanding farmer decision-making under risk and uncertainty has long been a central concern in agricultural economics, evolving from classical models to those that incorporate behavioral insights (Wuepper et al., 2023).

A key limitation in the existing literature on agricultural risk is its narrow focus on production risks, even though farmers face multiple risks that are closely tied to production outcomes (Komarek et al., 2020). This narrow focus obscures important nuances in the adoption

of risk management strategies and technologies. Chapters 2 and 4 of this thesis show that other risks are also highly salient to farmers. In Chapter 2, the most frequently cited risks include low crop yields (production), volatile input prices (market), reduced agricultural income (financial), illness (personal), price controls (institutional), and food insecurity (financial/personal). Among these, low yields, reduced incomes, and input price volatility contribute most to farmers' overall risk perceptions.

Gender differences in risk perceptions also emerge. For men, perceptions are primarily shaped by the perceived likelihood and severity of risks, consistent with the literature (e.g., Sullivan-Wiley and Short Gianotti, 2017). For women, perceived ability to cope with, or control, risks play a more prominent role, echoing Wilson et al. (2019) and van Duinen et al. (2015). This difference appears linked to underlying socioeconomic disparities in assets (as demonstrated also in Chapter 4), as well as non-cognitive factors such as locus of control and willingness to experiment with risky technologies; men are generally more willing to experiment with such technologies than women. These gendered differences may contribute to variation in households' capacity to adopt new technologies (see for example Dercon & Christiaensen, 2011), and are consistent with evidence from Haushofer & Fehr (2014), who show that psychological factors such as risk perceptions and preferences both shape and are shaped by economic status.

The salience of multiple risks among small-scale farmers suggests that risk management strategies and technologies capable of simultaneously addressing several risks are likely to be more attractive to farmers. Similarly, when farmers perceive a particular risk as highly relevant, they are more likely to adopt or invest in strategies and technologies that directly mitigate that risk (Kassie et al., 2017). For example, if low yields or high yield variability are perceived as major risks, farmers should, in theory, be more willing to adopt, or pay for, high-yielding crop varieties

(Adesina & Zinnah, 1993). The same logic extends to other desirable traits, such as drought or flood (waterlogging) tolerance and resistance to pests and diseases, all of which reduce yield variability.

Chapter 4 supports this argument. Many farmers preferred a multiple peril (MP) insurance product that protects against catastrophic losses from multiple risks. However, others preferred a single-peril (SP) product that fully covers losses from a single risk (drought), which they perceive as particularly severe and beyond their control. This divergence highlights that, even when facing the same underlying risks, differences in perceptions give rise to distinct preferences for risk management mechanisms, and perhaps for other agricultural innovations and technologies. The results suggest that risk management strategies tailored to farmers' heterogeneous risk perceptions and profiles may achieve higher uptake.

7.2.2. Information alone is insufficient for adoption; its delivery, framing, and target audience also matter

Information is crucial in the adoption process as highlighted in the diffusion paradigm of technology adoption (Ruzzante et al., 2020). For instance, Chapter 3 shows that farmers tend to place higher value (i.e., submit higher bids) on attributes they clearly understand or can readily relate to, or have prior experience with. This suggests that creating awareness and opportunities for farmers to experiment with new technologies is essential for learning about performance, appreciating the benefits of improved traits, and ultimately driving adoption. However, if providing farmers with opportunities to experiment with technologies can increase their demand for and adoption of those technologies, why then does the large adoption gap persist, despite numerous initiatives aimed at educating farmers and facilitating on-farm experimentation? The answer lies in how farmers learn and in the nature of the technologies themselves (see for example

Barham et al., 2015; Maertens et al., 2021), and different aspects of information. Although evidence shows that farmers learn effectively through experimentation or experiential learning (Janzen et al., 2021; Kondylis et al., 2017), the adoption gap suggests that even when such opportunities are available, external factors such as weather variability may prevent them from realizing yield gains, leading to misperceptions about the technologies' performance and quality (Maredia & Bartle, 2023; Michelson et al., 2021). When expectations are not met after experimentation, dis-adoption becomes likely (see for example Miehe et al., 2025). For the case of improved varieties, many farmers revert to familiar but lower-yielding varieties, resulting in low adoption rates and limited varietal turnover (Chen et al., 2022; De Groote & Omondi, 2023).

Effective extension should therefore shorten the feedback loop between use and outcomes, and be experiential at the same time (i.e., foster learning by doing). Game-based learning achieves both objectives. The findings in Chapter 5 revealed that though both game-based and narrative-based learning enhanced farmers' understanding of index insurance, game-based learning proved significantly more effective, consistent with earlier studies (Cai & Song, 2017; Janzen et al., 2021). This underscores the importance of how information is delivered (Baul et al., 2024; Dzanku et al., 2020; Kondylis et al., 2017; Van Campenhout, 2021) and partly explains why many information interventions fail to translate into sustained adoption. Future research should examine the most effective delivery channels for different types of information related to a certain technology such as awareness, usage instructions, technical aspects, or costs and benefits.

Adoption appears to depend on not only access to information, but also on the perceived quality of the technology (Chapter 5). While game-based learning improved understanding, it also reduced farmers' demand for insurance, whereas narrative-based learning had no significant effect. The decline in demand reflected farmers' experience of basis risk during the game. Once farmers

learn about technology's limitations, their willingness to adopt tends to decline (Chen et al., 2022; Miehe et al., 2025). This finding reinforces the role of perceptions: information shapes how farmers perceive both risks and technology attributes, and as discussed above, the learning modality matters. Chapter 6 further shows that framing of information and the target audience (i.e., value chain actor) also influence how information is interpreted and acted upon. While Chapter 5 focused on farm-level information constraints, Chapter 6 focused on information constraints faced by market actors.

Results from Chapter 6 showed that although information influenced behavior in general, the effect of framing varied between consumers and traders. For traders who are mostly profit-oriented, gain frames seem to be more persuasive. For consumers, for whom health is the primary outcome, framing may operate differently depending on perceived risk: if consumers believe they have already suffered health damage from contaminated maize, loss framing may be less persuasive as has been shown in other contexts (see for example Balew et al., 2025). Conversely, if they believe health effects are reversible, gain framing may be more compelling. The effectiveness of framing therefore seems to depend on the audience, perceived risk, and the link between risk and mitigating behavior (Rothman et al., 1997).

Two additional insights emerge from Chapter 6 regarding information interventions. First, the effect of the information campaign on maize quality faded after approximately three months, likely reflecting seasonality (i.e., the inflow of higher-quality maize into markets) and/or limited exposure, suggesting that the intervention did not reach sufficient saturation. This highlights the importance of timing (when to intervene) and frequency (intensity of the intervention) in the design of information interventions.

7.2.3. Willingness to pay seems not to adequately reflect farmers' preferences for agricultural innovations

Although WTP is commonly used to assess (potential) demand for agricultural innovations, it seems not to fully characterize farmers' preferences (Chapters 3 and 4). For example, Chapter 3 shows limited differentiation in WTP across forage varieties, despite each variety possessing at least one distinct trait. While "anomalies" in WTP and preferences might be caused by "irrelevant" factors, as documented in the literature (e.g., Ariely et al., 2003), Chapter 4 provides a clearer picture in the context of risk management innovations. Farmers' preference for the MP product becomes more evident when farmers are allowed to switch. Switching between products is not arbitrary; rather, it reflects aversion to tail risk and the role of precautionary behavior, dimensions of preference not captured by WTP measures alone.

This suggests that farmers' preferences are sensitive to the choice environment and may shift when there are alternatives. Evidence from (Shikuku et al., 2026) supports this: the paper shows that pastoralists were willing to incur costs over their WTP for default products to switch to preferred products, with information playing a key role.

In practice, farmers evaluate new technologies relative to familiar options (reference-dependent preferences). While the availability of alternatives can enhance attention to differences in attributes, it may also complicate decision-making and reduce welfare when choice sets become too complex (Greifeneder et al., 2010; Lleras et al., 2017; Scheibehenne et al., 2010). Such "shifting" preferences may help explain the gap between encouraging WTP estimates and observed adoption outcomes. Failing to account for these behavioral factors in ex-ante preference elicitation can therefore misguide policy and technology recommendations. Findings from Chapter 4 suggest

that incorporating structured choice tasks into preference elicitation can provide a more comprehensive understanding of farmers' preferences than WTP measures alone.

7.3. Limitations and implications for research

While this thesis extends knowledge on the technology-adoption puzzle among small-scale farmers, several limitations warrant attention and point to directions for future research. First, the relatively short time horizon over which the interventions were implemented limits the scope of inference. With additional resources, further data collection waves would have enabled a more comprehensive assessment of both short- and longer-term effects. In addition, Chapter 2 could have benefited from a longitudinal assessment of farmers' risk perceptions and how information, such as objective forecasts of future drought conditions, shapes these perceptions over time. Future research could build on this by explicitly modeling learning processes and examining how new information interacts with prior beliefs to influence behavior.

Relatedly, Chapters 3–6 would have benefited from additional treatment arms to better identify underlying mechanisms. For example, experimentally varying both access to and the type of information in Chapter 3 would have helped disentangle its causal effects on WTP for specific varietal attributes. The study could also have incorporated a treatment arm allowing for switching across varieties, as implemented in Chapter 4. Observing WTP before and after experimentation, when farmers have a more accurate assessment of costs and benefits, would provide deeper insights into both valuation and adoption dynamics. In Chapter 4, observing revealed demand for SP and MP insurance products following the switching exercise would similarly have strengthened the empirical conclusions. Moreover, comparing between- and within-subject valuation designs could have shed light on the sensitivity of WTP to this design aspect. Future research should seek to address these design limitations.

Second, across the intervention-based chapters, the analysis does not explicitly assess cost-effectiveness of the interventions relative to conventional approaches. For example, the relative cost-effectiveness of gamified versus narrative-based extension (Chapter 5), or of information-based quality signaling relative to alternatives such as laboratory testing, third-party verification, or certification (Chapter 6), remains an open empirical question. Incorporating cost-effectiveness analysis would be particularly valuable for informing policy design and scaling decisions.

Third, the findings reveal substantial heterogeneity in perceptions of risk, technology attributes, and preferences. While broadly consistent with the literature, these results may not generalize across contexts. Socioeconomic and biophysical conditions, as well as norms and cultural factors, are likely to shape perceptions of risk and technology attributes, as well as responses to information and behavioral interventions. Future research should therefore replicate and extend these analyses across diverse settings to generate more context-specific policy insights. More frequent data collection, combined with advanced data discovery approaches such as machine (and or deep) learning, could further enable the identification of farmer segments and improve the targeting of technologies and intervention bundles.

7.4. Implications for policy

A central policy message from this thesis is the need for a more holistic and integrated approach to addressing the multiple constraints underlying low adoption and persistent productivity gaps in smallholder agriculture. Adoption barriers are multidimensional, reflecting the interplay between risk, information, technology attributes, and market conditions. Accordingly, policy responses should move beyond isolated interventions toward coordinated strategies that address these constraints jointly or in a sequenced manner. The salience of multiple, interlinked risks, for example, suggests that integrated risk management approaches are likely to be more

effective. Approaches such as risk layering, which combines instruments to address risks of varying frequency and severity, and the bundling of complementary technologies (e.g., improved seeds, insurance, and extension) offer promising pathways. However, their effectiveness depends critically on enabling institutional environments that support coordination across actors and ensure long-term sustainability.

A second implication concerns the importance of incorporating behavioral insights into the design of interventions. The findings demonstrate that adoption is shaped not only by access to technologies and information, but also by how information is framed, delivered, and experienced. Evidence from this thesis, such as game-based learning and alternative information framing, underscores the potential of behavioral interventions to influence both understanding and decision-making. Interventions that account for, or seek to correct, behavioral biases in how risks and technologies are perceived, as illustrated in Chapter 4, should therefore be encouraged.

Third, the findings highlight the need to strengthen government regulatory frameworks and capacity, particularly in contexts characterized by informality. Weak quality assurance systems limit the effectiveness of both technology adoption and market-based incentives. For example, regulators should prioritize minimizing basis risk in index insurance products and ensuring the quality and reliability of key inputs such as improved seed varieties and fertilizers. Maintaining farmer trust is critical, as it is costly to rebuild once eroded. In this regard, ensuring that farmers receive accurate and consistent information about technologies is essential. While limited access to information remains a challenge, the spread of misinformation may be even more detrimental, as it can undermine trust and slow learning, thereby impeding both agricultural and broader economic transformation.

Relatedly, there is a need to better align the pace of technological innovation with farmers' capacity to learn and adopt. The rapid introduction of new technologies, such as improved crop varieties, combined with weak supply systems (e.g., delays in certification) and limited support for learning can undermine adoption. Policies should therefore emphasize structured dissemination, effective extension systems, and mechanisms that facilitate experiential learning.

Finally, the results underscore the importance of investing in data systems, feedback mechanisms, and stronger research–policy linkages. Given the heterogeneity in farmer perceptions and preferences, policies should be informed by continuous, high-frequency data that capture farmers' experiences with technologies. Establishing platforms through which farmers can provide feedback on technology performance would support more responsive and adaptive policy design. Advances in information and communication technologies (ICTs) and crowdsourcing approaches offer cost-effective opportunities in this regard. More broadly, sustained investment in research, alongside stronger collaboration between policymakers, researchers, and other value chain actors, is essential to generate context-specific evidence and support the scaling of effective interventions.

7.5. Closing remarks

For decades, research on the technology adoption puzzle in low-income countries has appropriately focused on small-scale farmers, given their large numbers, high vulnerability to climate change, and the central role of smallholder agriculture in rural livelihoods. This body of work and the evidence from this thesis has generated several important insights, including the role of behavioral biases (e.g., Wuepper et al., 2023), the implications of farmer heterogeneity for adoption (e.g., Arouna et al., 2021; Dercon & Christiaensen, 2011), and the dynamic nature of adoption processes, whereby farmers both adopt and dis-adopt technologies over time (Miehe et al., 2025).

Despite these advances, this thesis highlights the extent to which important questions remain unresolved. For example, it remains unclear how technologies can be scaled cost-effectively in the presence of substantial heterogeneity and multiple, interacting constraints. Relatedly, identifying the "sweet spot" for bundled interventions that jointly address key constraints without becoming prohibitively complex or costly remains an open empirical and policy question. The need for further research is therefore evident, especially given that research expenditure per farmer remains lowest in low-income countries (Suri & Udry, 2022).

At the same time, an increasingly uncertain funding environment complicates the expansion of such research. This places greater responsibility on governments in low-income countries to invest in research and development. It also calls for a rethinking of research and implementation strategies. Greater engagement with the private sector and other supply-side actors may be necessary to sustain innovation and scale. There is a need to move toward a more integrated analytical framework. Rather than treating existing paradigms of technology adoption as distinct or competing strands, future work should seek to harmonize these perspectives into a unified approach that jointly considers risk, behavior, information, and market dynamics. The evidence generated in this thesis supports the relevance of such an integrated paradigm.

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Summary

Agricultural innovations and technologies designed to enhance productivity and strengthen risk management in small-scale agriculture are pivotal for the economic transformation of low-income countries. Yet, for decades, adoption of such innovations has remained puzzlingly low despite their availability in most cases. There is no single binding constraint to the adoption of productivity-enhancing technologies and risk management strategies by small-scale farmers. Understanding this persistent "adoption puzzle" therefore requires a multidimensional approach.

This thesis focuses on the roles of agricultural risk, information, and informal markets in explaining the adoption puzzle. It conceptualizes technology adoption as a process that begins with farmers' perceptions of the risks they face, followed by matching available technologies to those risks, and ultimately selecting the technologies that address their most salient risks. However, the adoption story is not this trivial. Behavioral biases influence how farmers perceive risks and evaluate technologies even when opportunities for learning are available. Moreover, dynamics in informal markets, particularly information asymmetries around unobservable quality for both productivity-enhancing inputs and outputs, further complicate the process. Within this framework, the thesis addresses three key questions: i) Which risks and risk attributes are most important to farmers, and do risk perceptions differ between men and women? ii) How do farmers value technologies, and do these valuations reflect underlying preferences and risk perceptions? iii) Can addressing information frictions at both production and market levels unlock technology uptake?

The analysis of farmers' risk perceptions revealed that multiple risks are salient, extending beyond production to include market, financial, and personal risks. The thesis critiques the prevailing bias toward production-related risks and advocates for innovations and technologies

that address this broader risk spectrum through approaches such as risk layering and innovative bundling. It also finds that men and women perceive risks differently. Since risk perceptions strongly influence technology adoption, gender-responsive innovations must go beyond addressing the "symptoms" of inequality such as limited access to land, credit, and information to also account for the underlying psychological and structural factors that shape these disparities.

In exploring how farmers value technologies, the thesis focuses on improved forage varieties and index insurance. Willingness to pay (WTP) for improved varieties, like most crops, was below market prices but slightly higher for varieties with which farmers had prior experience. WTP did not differ significantly across varieties, likely because farmers did not pay attention to the subtle, unique differences each variety offered. This underscores the importance of providing farmers opportunities to experiment with new technologies so they can fully appreciate the unique "improvements".

Regarding index insurance, farmers expressed a strong preference for a multiple-peril product that covers major losses from multiple risks, rather than conventional single-peril products that insure against only one type of risk. The thesis shows that choice architecture influences technology decisions: farmers may exhibit "preference reversals" when introduced to alternative technologies. Consequently, relying solely on ex-ante WTP elicitations to inform pricing and subsidy policies risks overlooking important behavioral dynamics, oversights that may have significant implications for adoption.

Because learning takes time and outcomes are influenced by external factors such as weather, extension approaches that foster experiential learning and shorten the feedback loop between experimentation and results are crucial. This thesis tested game-based learning as an alternative to conventional narrative-based extension and found it significantly more effective in

helping farmers understand index insurance. Farmers exposed to high basis risk in the experimental setting showed lower demand for insurance, suggesting that they better grasped the product's limitations compared to those who only received information about basis risk.

The thesis further examines the potential of using observable quality attributes as proxies for unobservable ones, focusing on aflatoxin contamination in maize in addressing incomplete information on quality in informal markets. Providing market actors with information on the link between kernel integrity and aflatoxin contamination led to modest improvements in maize quality in informal markets. Sales volumes of high-quality maize increased, although prices remained unchanged, and the effects faded within three months. This fade-out highlights the need for sustained information campaigns and complementary dissemination channels, such as mass media, to reinforce learning and behavioral change.

In conclusion, understanding farmers' risk perceptions is a crucial step toward explaining farmers' heterogeneity in technology adoption. While information plays a central role in adoption, the mode of delivery matters greatly: farmers learn best through experiential modalities that reduce the gap between experimentation and outcome realization. Finally, dynamics within informal grain markets in low-income countries may hinder the development of market-based incentives for quality improvement even when actors have information on quality. More research is therefore needed to identify sustainable market mechanisms that can drive on-farm adoption of quality-enhancing technologies.

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Jamleck Osiemo Oroko
Wageningen School of Social Sciences (WASS)
Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1 Managing a research project			
WASS PhD Introduction	WASS	2019	1
Writing Research proposal	WASS, DEC	2020	6
Review of scientific paper: "Determinants of adoption of livestock and aquaculture innovations for low emissions food systems transformation in Kenya: A review"	Outlook in Agriculture	2025	1
Review of scientific paper: "Holistic decision support for enhanced child nutrition: School Garden interventions in Vietnam"	Humanities and Social Science Communications	2025	1
Review of scientific paper: "Farmers' premium expectations for adopting precision pesticide technology: An empirical analysis in China's apple production"	Scientific Reports	2026	1
"Willingness to pay and switching preferences for actuarially equal index insurance products"	Centre for the Study of African Economies (CSAE) conference, Oxford, UK	2025	1
"Information and food quality in informal markets: Experimental evidence from Kenya"	Advances with Field Experiments (AFE) Conference, University of Chicago, USA	2025	1
"Information and food quality in informal markets: Experimental evidence from Kenya"	CSAE conference, Oxford, UK	2026	1
A2 Integrating research in the corresponding discipline			
Advanced Econometrics, AEP 33806	Wageningen University	2020	6
Impact Assessment of Policies and Programmes, DEC 32806	Wageningen University	2020	5
Behavioural and Experimental Economics, UEC 51306	Wageningen University	2020	5
Advanced Qualitative Research Methods, GEO 56806	Wageningen University	2021	5
Risk analysis and risk management in agriculture	WASS	2019	3
B) General research related competences			
B1 Placing research in a broader scientific context			
Mathematics theory and practice	WASS	2020	3
Research methodology, from topic to proposal	WASS	2020	4

B2 Placing research in a societal context			
"Is equal similar? What we learn from farmers' WTP for and switching behavior between equal index insurance products"	Dutch Development Economics (DuDE) PhD workshop, Wageningen	2024	1
C) Career related competences/personal development			
C1 Employing transferable skills in different domains/careers			
Scientific writing	Wageningen in'to Languages	2020	1.8
Total			**45**

*One credit according to ECTS is on average equivalent to 28 hours of study load

