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The Influence of Framing and Recent Experience on Farmer Choices in Experimental Games Depicting Risk-Reducing Agricultural Technologies

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THE INFLUENCE OF FRAMING AND RECENT EXPERIENCE ON FARMER CHOICES IN EXPERIMENTAL GAMES DEPICTING RISK-REDUCING AGRICULTURAL TECHNOLOGIES

By

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An Abstract of the Thesis Presented
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Climate change is a major threat to food security, particularly in low and middle-income countries that are highly dependent on staple crops for subsistence. The vulnerability of staple crops, like maize, in the face of climate change, is increasing due to the increasing frequency of droughts. This thesis aims to evaluate two mechanisms through which farmers may be more willing to adopt new technologies that increase their resilience to climate change: First, I evaluate the effectiveness of a new virtual maize farming game as a learning tool to teach farmers about the outcomes they could obtain under different weather events when adopting new technologies, specifically drought tolerant maize seeds and satellite-based index insurance. Second, I test the effectiveness of framing messages that induce farmers to evaluate prospects not just by the individual utility they provide but also in terms of the utility they may perceive through their family and community well-being. Thus, both, the game and framing messages created for this thesis are meant to nudge farmers' behaviors, inducing farmers to choose the new resilience-enhancing technologies.

As part of a bigger research project, the game was developed and tested with a sample of maize farmers in Mozambique in the form of a framed field experiment. Local data were collected to calibrate key parameters of the simulated game. Enumerators collected sociodemographic data of farmers participating in the experiment through a survey. A subset of the sample for the survey data was randomly selected to participate in one of the three versions of the virtual game, where each version differs by the framing message to which the farmer was exposed. A paired t-test and multinomial logit models were used to test the role of experience in the game and the framing messages in changing farmers' behavior in the short term, within the game itself.

I find that experience within the virtual maize farming game produces changes in farmers' in-game behavior. Notably, experience with simulated drought events are determinant in the learning process. Additionally, those exposed to the framing messages related to family and community domains are more likely to adopt the new technologies compared to those exposed just to the framing related to the individual domain. Moreover, the impact of the framing varies depending on farmers' experiences with droughts in the real world as well as during the game.

These results indicate that simulated experiences through games could be useful tools to introduce new technologies to small farmers. Furthermore, introducing framing messages in these games can intensify the rate of acceptance and adoption of technologies that may help farmers to be more resilient in the face of climate change. These results only show changes in farmers' behaviors in the short term. Further research is needed to evaluate the long-term impacts of this experiment.

Keywords: Agriculture, resilience, climate change, Expected Utility Theory, behavioral economics, framing, game.

DEDICATION

Going through graduate school as an international student, in a foreign language and a different culture from my own, would not have been possible without the great support I have from the community I built in Maine and from my loved ones who supported me from a distance. I think I have never written as much in English as I have done for this thesis, but definitely, the multiple talks and revisions I have in the process with my advisor Jonathan Malacarne were key for guiding me in building my idea and this final scientific piece. I am very grateful for having Jonathan as my advisor, I learned a lot from him. I also want to thank all the rest of my committee and professors at UMaine who taught me a lot and supported me during grad school. For my Maine community, I am very grateful for having found such an amazing group of friends, that helped me to relieve the stress of the challenges I had during my time in Maine and make everything smoother and happier. For the people who supported me from a distance, I want to thank my parents for always being there for me, through calls every week and for giving me their wisdom and strength in the moments I need it the most, even though at the beginning they did not understand why I decided to move to a different country and leave my job in Colombia in order to go back to school. I also want to thank all my friends in Colombia who always were there checking on me from a distance and the ones who help me with their recommendations on the application process for grad school. I want to particularly thank Vanessa Olaya, Andres Abadia, and Jorge Alexander for helping me out with the biggest challenge I had on this thesis, which was learning and developing an app in Android Studio for the implementation of the game needed for the fieldwork. Although in the end, this app was not the final version implemented on the field, learning how to use Android Studio with the help of my Colombian friends was a great part of this process. I also want to thank my husband Matthew Hyde, and his family for all the support they provided me to manage things in the U.S., for helping me in the transition from Colombia to a new environment, and for being always there. For my dear husband, thank you very much for everything, for your infinite support and love in this process from the beginning to the "end" —although we have already planned so many other adventures to go from now on. I am very proud of what we both have accomplished so far. One of the best lessons I have from these two years of distance relationship is that no matter how far people are, there are always ways to make people feel you are close to them. Finally, I just want to say that we all have fears and challenges that make it harder to achieve our goals, but all of us are capable of doing more than we think we can. Expanding that frontier of what we know we are able to do is worth it, you may surprise yourself as I have surprised myself.

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CHAPTER 1

INTRODUCTION

Climate change is a major concern for policymakers worldwide. Extreme natural events like hazardous convective weather, floods, and droughts, are becoming more intense and frequent. Weather-related losses from both agriculture and fisheries have increased since the latter half of the 20th century, affecting food production and food security(Riebau and Fox, 2005; Melillo et al., 2014; Powell and Reinhard, 2016). El Niño induced droughts of 2015 and 2016 are clear examples, with severe food security consequences for Southern Africa and Central America (Hove and Kambanje, 2019; Nobre et al., 2019).

Researchers and stakeholders are interested in mitigating the impacts of climate change through new technologies. Drought-tolerant seed varieties and index insurance are some of the promising options to help farmers to be more resilient (Kostandini et al., 2009; Shin et al., 2022). However, the lack of experience with these technologies is one of the obstacles to their adoption when available (Takahashi et al., 2020; Mariano et al., 2012; Nhemachena and Hassan, 2008).

With the goal of contributing to the research that helps to close the gap between the availability of crop technologies and their adoption, this thesis will explore how the implementation of a simulated game can alter farmers' decision of whether to adopt a new technology. The following chapters will provide insight into how this type of intervention with small farmers can help mitigate the impact of extreme weather events on farmers' food production and livelihoods. For this purpose, we conducted a framed field experiment (Levitt and List, 2009) in the summer of 2022 in which a sample of small farmers in central Mozambique were exposed to a game that simulates the seasonal crop environment. The game simulates a 10-year period during which farmers make repeated decisions regarding input choice. Further, the game included framed messages meant to highlight different domains through which input choices might affect well-being. Throughout this thesis, I will study how both the simulated experience and framed messages during the game might accelerate the adoption process.

Agriculture is very sensitive to temperature and extreme weather events, especially during key growth phases of crop development (Motha, 2011). As the FAO mentioned in its Koronivia Joint Work on Agriculture (KJWA), "agriculture absorbs 26 percent of the economic impact of climate disasters, rising to 83 percent for drought in developing countries" (FAO, 2021). Climate change can generate new challenges related to diseases and pests that destroy crops. It can also affect soil features, like increasing concentrations of CO2, which reduces the availability of protein and essential minerals. This can have a negative impact on the yield of the world's most important staple crops, like rice, maize, potatoes, and wheat. Furthermore, those effects may compromise the nutritional security of households that rely on these staple food, affecting the well-being of people who are unable to diversify their meals (Ziska et al., 2016). It is expected that climate-related disruption in food supply will leave millions of people under marginal conditions of food security by 2050 (Swinnen et al., 2022). Nevertheless, the impact of climate change differs by region and type of crop (Pörtner et al., 2022).

Extreme weather events disproportionately affect the most vulnerable populations. As mentioned by Gamble et al. (2016), vulnerability to weather variability can be understood from three elements: exposure to stressors that adversely affect people; people's sensitivity to those exposures; and their adaptive capacity to respond to shocks. However, the sensitivity of different communities depends on factors such as geography and environmental conditions. Furthermore, people's adaptive capacity differs based on social and economic conditions, which influence their access to innovation, diversification of goods and services, and human capital. This often leaves low-income populations without access to the resources to overcome climate-related difficulties and build resilience (Levy and Patz, 2015; Leichenko and Silva, 2014; Hope Sr, 2009).

The productivity of maize, one of the world's major staple crops, has already been negatively affected by climate change in low-income regions in Sub-Saharan Africa, Northern Africa, and Latin America (International Food Policy Research Institute, 2022). The increasing frequency of droughts is expected to put additional pressure on the lower tropical latitudes where rainfed agriculture plays a dominant role (Rockström et al., 2010). These consequences are felt most strongly by rural communities dependent on subsistence production (Altieri et al., 2008).

Despite continued total factor productivity (TFP) growth in agriculture in the last decade, climate change has kept the sector from reaching its potential. Starting with 1961 as a baseline, Ortiz-Bobea et al. (2021) estimated that global TFP in agriculture would be 21% higher in the absence of anthropogenic climate change. This estimated gap in the growth of agricultural TFP is larger in historically warmer areas. Regions like Africa and Latin America and the Caribbean have seen the largest effects, facing a reduction in their TFP by 24% and 34% respectively compared to what could have been without anthropogenic climate change. FAO (2009) also reported that the rate of growth in cereal yields per year has been reduced from 3.2% in 1960 to 1.5% in 2000. Accelerating the transition of technology into more resilient agriculture is needed, especially in the most disadvantaged regions (Pörtner et al., 2022).

Synergistic strategies for addressing adaptation and mitigation can foster more resilient crop production in the face of unpredictable weather events (Carter et al., 2017; FAO, 2009). Some researchers have already suggested methods to improve crops' resilience, like promoting genetic diversity and using new seed varieties that are more resistant to extreme weather conditions (abiotic stressors) and insects and diseases (biotic stressors). These stress-tolerant varieties can reduce losses by 23% of the attainable yield in some of the major cereal crops (Dar et al., 2013; Tester and Langridge, 2010; FAO, 2009). Increasing investment in agricultural research and development is important to facilitate the technological transition for low and middle-income populations to increase their productivity and climate resilience. This approach should be complemented with investment in rural infrastructure, stronger institutions, better transfer of information, and farm policies (FAO, 2009). Thus, reforming policies and market incentives must be integrated into these strategies to encourage long-term food security (Pörtner et al., 2022; Cai et al., 2020; , IFPRI; Steensland, 2019). Moreover, policymakers must reduce barriers for small producers, like budget constraints, access to financial credit, and market access issues (Takahashi et al., 2020). High-income nations may play an important role in this transition thanks to their capacity to transfer innovations. Importantly, facilitating access to and adoption of new varieties could significantly improve crop yields, household net income, and, thus, small-farmers well-being (Boucher et al., 2021; Takahashi et al., 2020).

Although making technologies accessible may be necessary, it is not sufficient to achieve high rates of adoption. Small farmers tend to prefer traditional practices and, even when newer technologies are available, may choose to manage their crop production in the traditional way. As mentioned by Lunduka et al. (2012), besides yields, farmers also value in their local seeds other features like taste, texture, storability, and processing traits. Farmers with a strong attachment to their local varieties would be the slowest to transition to the new technology, as well as highly risk-averse farmers who have not experienced the benefits of the technology. Nevertheless, once a risk-averse farmer has experienced the maximum return of the new technology, which occurs in “bad” weather conditions where it most strongly outperforms traditional methods, then they may end up adopting the technology faster than their risk-neutral counterparts (Lybbert and Bell, 2010; Brick and Visser, 2015).

Given the randomness of weather events, it is hard for an individual to gain experience in the short term with the performance of new agricultural technologies. Particularly, for stress-tolerant seeds and index insurance, it is difficult to see their benefits unless producers test them under extreme weather conditions, where improved seeds outperform traditional seeds and index insurance may pay off. This lack of direct experience frames farmers' investment decisions. People from different contexts may have different experiences regarding the return of these technologies and thus, their constructed beliefs on the technologies' performance are based on a different set of experiences (Malacarne, 2019). Lacking direct experience, farmers may also try to learn about the performance of new technologies from their neighbors Foster and Rosenzweig (1995), however, this source of information faces the same challenges.

It is under this scenario that simulated learning strategies can allow farmers to gain a better understanding of the performance of new seed varieties and set more accurate expectations, thereby leading to more informed decisions about adoption. Additionally, the simulated learning strategies may also help homogenize community beliefs about seed variety performance and teach farmers about how index insurance work. In this thesis, I will assess the impact that learning through simulated experiences can have on small farmers' behaviors. But before doing so, I will consider two theories of decision-making under uncertainty — Expected Utility Theory and Prospect Theory — along with behavioral economics insights derived from experimental economics, exploring how these theories apply to small farmers' behaviors.

Behavioral researchers have increased the use of experimental economics since the mid-1960s to understand farmers' perceptions and decisions and to understand what type of interventions can influence them the most (Dessart et al., 2019; Levitt and List, 2009, 2007). This field of study embraces experiments conducted in laboratories through randomization of the subjects and in naturally occurring environments that allow researchers to test hypotheses on human behaviors, although the external validity of experiments and games need to be treated carefully(Voors et al., 2012; Torres-Guevara and Schlüter, 2016). Experimental economics has proposed new explanations of behaviors from more descriptive theories than classical economic theory. The descriptive theory I am most interested in incorporates the idea that humans are boundedly rational, meaning that people tend to reduce the mental effort required to choose between options (Kahneman, 2011, 2003). This may affect the individual's optimization problem, where the option selected may not be the decision that maximizes the subject's expected utility. Instead, the individual may try to minimize the cost of mental burning while still satisfying her needs.

This thesis will contribute to our understanding of the relevance of experimental games and framing messages as tools to disseminate future agricultural technologies among farmers. There is a gap in the literature on how framing can affect the technology adoption decisions of maize farmers, though the question has been explored for farmers in other scenarios (Vollmer et al., 2017; Davidson and Goodrich, 2021; Andrews et al., 2013). Specifically, this thesis will contribute to understanding small farmers' beliefs about the performance of traditional and drought-tolerant maize (DTM) varieties through the development and implementation of a game. Additionally, the game developed is meant to teach farmers how complementary products like satellite-based index insurance (II) can be part of a resilience-enhancing investment strategy. Overall, the game allows farmers to quickly experience the benefits that both DTM seed and index insurance can have on their resilience to uncertain weather events and, therefore, their household and community well-being.

This thesis consists of four chapters. The first chapter consists of the introduction for this thesis, here presented. Chapter 2 explores the conceptual model under which the experiment was constructed. Here, I build on four key concepts: 1. the neoclassical foundation of behavior under the framework of expected utility theory (EUT), 2. an alternative explanation from behavioral economics and prospect theory, 3. the effects of learning-by-doing, and 4. the nudge effects of messages that are meant to frame behaviors. I will demonstrate how the simulated game created for this experiment, which promotes learning by virtually doing, could motivate people to adjust their beliefs and expectations and produce changes in their behaviors and investment decisions. Furthermore, I will explore how framed messages may accelerate the change in behavior. The chapter concludes with a set of hypotheses that will be tested empirically in Chapter 3.

Chapter 3 presents the motivation, development, implementation, and results of the game, which was ultimately deployed as part of a framed field experiment in Mozambique with a sample of 275 small farmers. Specifically, here I describe: 1. the rationale of implementing a game to influence behavior, 2. the instruments and game developed to run the experiment and how they relate to the conceptual model, 3. a description of the sample with whom the game was implemented, 4. a description of how farmer choices evolve based on their experience within the game, and 5. empirical tests of the hypotheses developed in Chapter 2. Finally, Chapter 4 opens the discussion and concludes.

CHAPTER 2

CONCEPTUAL MODEL

2.1 Introduction

Choice theory has been widely analyzed by neoclassical economists from the utility maximization and cost minimization perspectives. Most of the time, the outcomes obtained from the decision-making process depend on stochastic external factors, leading to conditions of uncertainty. In addition to uncertainty, decision-makers do not always know the full set of possible outcomes or their associated probabilities with perfect precision. Instead, they are forced to make decisions based on their subjective expectations, using their experience and the experience of those around them as best as possible.

In this chapter, first I will discuss some of the insights that behavioral economics has provided by the experimental observations of subjects' behavior under uncertainty. Subsequently, I will present two choice theories that seek to explain how individuals make decisions. First, I will present the general decision-maker utility maximization problem under the umbrella of the expected utility theory (EUT). Then, I will discuss some of the factors that generate noise in understanding behaviors from EUT. Second, I will present a more descriptive explanation of behaviors from prospect theory (PT), which can shed light on some of the situations in which the axioms of EUT have not been confirmed in daily life. Using these theoretical frameworks, I will discuss the decision process in the context of agriculture, where farmers have to choose what type of inputs to adopt. Specifically, I consider the case where farmers have to decide whether to invest in new crop technologies based on their subjective beliefs about the set of possible outcomes and their respective probabilities. Finally, I will propose pathways through which an experimental game providing virtual experience and behavioral nudges might affect farmers' decision-making process.

2.2 The Decision Process

2.2.1 Some Behavioral Economics Insights

People make choices all the time. Some of these choices occur in precise, well-understood scenarios, where the decision-maker knows exactly what outcomes will follow from her actions. More often, people face uncertain scenarios. The uncertainty may arise from outcomes being influenced by forces outside the decision-maker's control — such as chance or the actions of other decision-makers —. Or, the uncertainty may arise from the decision-maker lacking experience with some aspect of the choice at hand. These factors make decision-making difficult and people respond to this challenge in different ways. It is unsurprising, then, that many of the theories of behavior in economics fail to fully explain the decisions of real-world actors.

These challenges are highly relevant to this thesis, which primarily deals with farmers. In the context of a farmer deciding what inputs to use on their land, a number of explanations have been proposed to explain decisions that seem inconsistent with traditional economic models of utility maximization. Just a few proposed explanations include incomplete information regarding how to implement new technologies (Foster and Rosenzweig, 1995); uncertainty or lack of knowledge regarding the outcomes that can be obtained and the probability of occurrence associated of those outcomes (Cerroni, 2020); a desire to avoid the possibility of regret (Zeelenberg and Pieters, 2007) (for e.g. if the market rejection of the product due its new features if any, like color, size, and taste); or fear of the unknown (Carter, 2016). Moreover, it is well established that people have strong preferences for certain outcomes (Druckman and McDermott, 2008) and options that are already familiar to them (Kahneman and Tversky, 1979; Brick and Visser, 2015), even if new technologies may have higher expected returns.

Notice that all of these factors that put a psychological barrier in the adoption initiative are connected to the lack of experience with the new technologies. This can be from both a lack of individual experience and a lack of experience from peers or people that are influential over the subject's decisions and who can transfer the information (Valente, 1993; Foster and Rosenzweig, 1995). Nevertheless, the learning effects may produce either knowledge spillovers or learning externalities, where the former implies a change in the productivity and intrinsic behavior of the individual, produced by the direct impact on the individual's knowledge, and the latter connects the idea of behaviors being altered not for intrinsic motivations but for social pressure and external effects.

Given the relevance that experience can have in reducing the mental barriers to adoption, it is important to understand how this lack of experience with new technologies can be managed. In the more general settings, one alternative is for the individual to be exposed to the new technologies and gain experience over time, hence gaining information and knowledge from personal experiences. This information gain could be difficult under scenarios where the outcomes are dependent on uncertain and infrequent random events, like weather, delaying the more accurate evaluation of the improved technologies. However, others may play an important role in transferring information, generating learning spillovers that can affect someone's decision-making process.

Building upon the second case, people may incorporate others' experiences in their decisions because either they do not have enough information to decide what to do or they already trust other people as sources of information. It has been observed that, whenever people do not know what to do, they are more sensitive to the behavior of the majority. This is especially true if this is a strong social identity or they are in close proximity to the group (Goldstein et al., 2008). Additionally, people like to feel they belong to a group or that they are accepted in a group. Therefore, if there is an alternative that is more likely to be approved by the group that someone belongs to, then people will tend to choose that option (Leary et al., 1995). On the other hand, people may base their decisions on recommendations from their peers based on trust. Taking a decision on the bases of trust implies confronting a decision problem where there is a likelihood of regretting a negative outcome (Luhmann, 2000). Trust may come from having previous good advice from the source or because they consider them experts in the field related to the choice problem — namely technical trust — or because of shared social norms and values — normative trust — or for convenience and interests involved — strategy trust — (Ramírez-Gómez et al., 2020).

Importantly, knowledge spillovers do not necessarily translate into individual learning, behaviors can be modified just by conforming to what others do (Foster and Rosenzweig, 1995). People may just decide to mimic some behaviors from others as a cultural option or other heuristic ways to solve their choice problem but may not internalize how the options work and how to optimize their outcomes (Wuepper et al., 2023). This is also connected to the idea that people prefer to *think fast* for most of their daily problem tasks, trying to avoid mental burning (Kahneman, 2011). An easy way to decide seems to be to follow what peers are doing. In conclusion, people can either learn by getting directly involved in a task that relates to the concept of learning by doing, or indirectly by learning from others in their network.

On the other side, learning itself implies that the new information received would be incorporated by the subject in their future decisions. Furthermore, decisions may be taken evaluating a sequence of outcomes over time instead of considering just a single outcome result. It has been shown that people tend to react differently depending on which of these ways the decision problem is presented (Loewenstein and Prelec, 1993). As a decision problem with a single outcome, people decide to choose their preferred option. As a sequence of outcomes, people may want to feel that their wealth or happiness is increasing over time versus decreasing or stable outcomes. This promotes the idea that people have memory and they will compare their expected outcome for a current decision regarding the real outcomes obtained before. Furthermore, recent outcomes may be the ones that influence the most current decisions since people want to increase their wealth relative to their current situation. This is particularly true in cases when the evaluated periods people are comparing are closer to each other, making stronger the preference for improvement than discounting effects. This is known as *the magnet effect* (Loewenstein and Prelec, 1993). Something to think about is that this time distance between the outcomes is shaped by the context. In the case of agricultural outputs and profitability, a one-year lapse seems to be a very rational period of time to be considered a short period, since some of the staples crops like maze take around a year to see the profit, given the time it takes the crop to be ready to harvest and out in the market.

To see this in the context of agriculture, imagine a situation where an individual face different sets of options for multiple time periods. In each period, there are random exogenous events that may affect the outcome. It will take the person a while to realize under which circumstances they may obtain the best result from each available option. Thus, initially, the person may select the option that is the most familiar to them. Going back to the concept of emotions, people may not necessarily move on to a different option given the bad outcomes obtained from the familiar decision. Since that is all they have experienced so far in their lives. Here social networks and the diffusion of information through media and interpersonal relationships play an important role to make the subject consider other options.

People use their current knowledge to evaluate the outcomes that a decision can bring. Once the results of a selection are observed, that knowledge must be updated. The observed outcomes could be aligned with the decision-maker's expectation or could be above or below the initial expectations. If the result is worse than expected, the decision-maker may experience a feeling of regret and may be more willing to select a different option to avoid the feeling of regret again (Zeelenberg and Pieters, 2007). If their expectation is exceeded, the decision-maker may be more willing to explore new options and will continue adjusting their expectations according to those new experiences. Therefore, if the experience with the new option is positive, then the individual may be more willing to discard the familiar or *status quo* option and opt for the new option.

In the following two sections, I will describe in detail the expected utility theory (EUT) and prospect theory (PT) for a discrete choice problem in an uncertain environment. I will pay particular attention to how the two theories deal with or fail to deal with some of the general decision-making behavior described in this introduction. To set the stage for the empirical application in Chapter 2, I will also highlight where individual-specific, subjective beliefs and learning might enter into decision-making under both theories.

2.2.2 The Decision Process from the Lens of the Expected Utility Theory

EUT suggests that agents will choose from a set of options the risky prospect that maximizes their expected utility. Since the decision-maker does not know exactly what the outcome of their decision is going to be, they base their decision on the expected utility of the lotteries they face (Moscati, 2018).

For the general setup of this theory, define $\boldsymbol{L}$ as the set of K simple lotteries. A given simple lottery, L_k, is defined by the possible outcomes, x_n^k, reachable under the lottery and the probabilities, p_n^k, with which these outcomes occur. I define the simple lottery, L_k in which there are N possible outcomes as:

$$L_k = (p_1^k, ..., p_N^k; x_1^k, \dots, x_N^k)$$

Where $\sum_n p_n^k = 1$ for any of the K lotteries in $\boldsymbol{L}$.

Furthermore, define the expected utility $U : \mathbf{L} \to \mathbb{R}^+$ as:

$$U(L_k) = \sum_n p_n^k u(x_n^k)$$

And let $U(L_k)$ represent an individual's preferences over simple lotteries. That is, for any $i, j \in K$, $L_i \succeq L_j$ if and only if $U(L_i) \geq U(L_j)$, .

Note that the expected utility of a lottery is written as the weighted average of the utilities from the various outcomes reachable under the lottery. The weights assigned to each outcome x_n are determined by the probability of occurrence. However, individuals may not know the objective outcomes reachable under a given lottery or the probability of their occurrence. The individual is thus forced to use their subjective probabilities and payoffs when making decisions. I will discuss the implications of this for my particular context in more detail below.

Some important assumptions and axioms need to be held under the EUT in order to explain behaviors. [1] However, for the purpose of this thesis, I will focus just on some of those assumptions. Notably:

- Invariance: This assumption is important to state consistency in the agent's choice. If lotteries L_i and L_j have the same probabilities distribution of outcomes and the same possible outcomes, then $U(L_i) = U(L_j)$ regardless of how the lotteries L_i and L_j are presented or described. Thus, the decision-maker should always be indifferent between both alternatives ($L_i \sim L_j$), even if the alternatives are presented in different ways.

- Independence: This axiom belongs exclusively to the theory of choices under uncertainty. It establishes that the preference order of $L_i \succeq L_j$ should not be affected when a third lottery, let's say L_m, is mixed with both lotteries. Thus $L_i \succeq L_j$ if and only if $\alpha L_i + (1-\alpha)L_m \succeq \alpha L_j + (1-\alpha)L_m$ with $\alpha \in (0, 1)$. This axiom is derived from the fact that, under EUT, the utility associated with each lottery is linear in probabilities.

[1] Von Neumann and Morgenstern (1947), Tversky and Kahneman (1989), Mas-Colell et al. (1995) and Gollier (2001) describe the following assumptions and axioms: Cancellation; Transitivity; Dominance; Invariance; Continuity; and Independence.

Additionally, agents' decisions under EUT also involve the consideration of asset integration and risk aversion (Lengwiler, 2009; Kahneman and Tversky, 1979):

- Asset integration: It indicates that people will choose a prospect L_i if and only if the utility level of adding the prospect to one's current assets is higher than the utility provided by the current assets or level of wealth itself. Thus,

$$U(p_1^i, p_2^i, \ldots, p_N^i; w_0 + x_1^i, w_0 + x_2^i, \ldots, w_0 + x_N^i) > U(w_0)$$

.

- Risk aversion: This condition of decreasing marginal utility allows us to have an interior solution for the maximization problem of the decision-maker. This type of preference guarantees a concavity in people's utility function such that $U'(L_k) > 0$ and $U''(L_k) < 0$, indicating that the utility perceived from a certain prospect is higher than the utility of a risky prospect that drives to the same expected outcome.

The following equation represents the expected utility that any prospect L_k available brings to a decision-maker under a discrete choice problem:

$$U(L_k) = \sum_{n=1}^{N} \rho_{ni} \cdot u_i(x_{ni}), \qquad x_{ni} \in X; n = 1, 2, ..., N. \tag{2.1}$$

In Equation 2.1, x_{ni} represents a vector with the possible N outcomes for the prospect L_k, where the sub-index i represents the individual's subjective beliefs regarding the realization of the outcomes. Similarly, ρ_{ni} may be defined by the individual as a mix of subjective and objective probabilities of occurrence for each possible outcome x_{ni}, where $\sum_{n=1}^{N} \rho_{ni} = 1$. The subjective probability is defined by the best guess of the individual conditional on factors that could influence the result — like their experience — and the objective probability is based on the historical frequency of occurrence. The probabilities assigned to a prospect are mutually exclusive so that only one of the outcomes will occur (Wetzstein, 2013). The utility level associated with each outcome is defined by u, also known as the preference functional, and it belongs to the positive domain $\mathbb{R}^+$. Here I assume that utility is defined as follows:

$$u_i(\cdot) = \quad x_{ni}^{\lambda_i} \tag{2.2}$$

Where $0 \leq \lambda \leq 1$ represents a risk-averse decision maker. The function U_i allows the decision-maker to rank lotteries in accordance with their preferences and therefore, state their choice. Here I allow preferences to vary by individual i. In summary, the ordinal expected utility of a prospect defined by Equation 2.1 represents the weighted averages of the cardinal utilities perceived for each possible outcome over all states of the world, as the expected utility is linear in the probabilities ρ_{ni}.

When the decision-maker faces the discrete problem of choosing a prospect among a set of options, the decision-maker evaluates each prospect and defines their expected utilities as established in Equation 2.1. Here, the decision-maker will select the option that provides the highest expected utility given their constraints. I will focus on the discrete choice version of an individual decision problem because it represents the type of choice problem covered in this research. Therefore, under a discrete choice problem, for every prospect L_h and L_j, with $h \neq j$, the problem of deciding which prospect to choose will be satisfied by the inequality 2.3.

$$U(L_h) \geq U(L_j) \qquad \forall j \neq h \tag{2.3}$$

This setup under the EUT is very useful to analyze people's decision-making process and it has far-reached important insights in both economic theory and empirical content. It provides a valuable rule guiding about what subjects' behavior should be under plausible assumptions (Friedman and Savage, 1952; Lengwiler, 2009), the reason why I consider the

EUT in this research. Nevertheless, this normative behavior has shown to be not followed in some empirical observations in the decision processes.

As has been observed in many social science experiments, choices can be influenced by context (Blom et al., 2021; Carlsson et al., 2021; Druckman and McDermott, 2008; Bonan et al., 2020; Kahneman and Tversky, 2000) and heuristics (Gigerenzer and Gaissmaier, 2011; Kahneman, 2011). There are some popular paradoxes that also call for a search for a complementary theory to explain behaviors, like Allais' paradox (Allais, 1979) and Machina's paradox (Machina, 2009) that contradict the independence axiom.

Often, inconsistency in decisions, whereby the option with the highest expected utility is not prioritized, is selected due to multiple reasons among which we can find the salience of other options, social pressure, an individual's emotions such as stress and enthusiasm, among other conditions discussed before from behavioral economics. Additionally, people tend to overweight extreme random and unlikely events, a behavior that is explained by the rank decision-dependent utility model (Tversky and Kahneman, 1992). These features that may affect the decision-process of EUT could be better approximated by the framework of Prospect Theory (PT). Section 2.2.3 will present in more detail this approach.

2.2.3 The Decision Process from the Lens of Prospect Theory

Multiple experiments have shown that context matters and how presenting the same choice problem in different ways can alter subjects' final decision. Furthermore, the emotions of human subjects, whether induced or not, can modify the impact that framing messages have on risk preferences and choices, as well as the level of confidence the subject has in those decisions (Druckman and McDermott, 2008). This additional piece of *confidence* may also have implications for future decision rounds, depending on whether the outcome corresponds to the expected result.

Tversky and Kahneman (1981) developed what later became a classical experiment under the theoretical framework of Prospect Theory, where the same expected outcomes are subjectively evaluated differently depending on how they are framed, in terms of gains or losses. [2] As predicted by prospect theory, changes in the description of the same problem (from gain to looses or vice versa) changed the way in which an individual perceived the outcomes of the prospects available, leading to inconsistencies in their decisions. Tversky and Kahneman (1989) summarize some empirical violations of the axioms normally used under EUT (see Table 2.1). Therefore, I present a descriptive theory representing subjects' beliefs and preferences, focusing on the alternatives proposed by behavioral economics, specifically prospect theory.

Table 2.1: Summary of Empirical Violations and Explanatory Models. Source: Rational Choice and Framing Decision (Tversky and Kahneman, 1989).

Tenet	Empirical violation	Explanatory model
Cancellation	Certainty effects	All models
Transitivity	Lexicographi semiorder; preferences reversals	Bivariate models
Dominance	Contrasting risk attitudes; subadditive decision weights	Prospect theory
Invariance	Framing effects	Prospect theory

Under prospect theory, the individual has a subjective evaluation of the alternatives, interpreted as gains or losses relative to a reference point, such as their status quo or current level of wealth (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Shin et al., 2022). Equation 2.4 represents the value function that subjects use to evaluate a prospect under this framework.

$$V(L_k) = \sum_{n=1}^{N} \pi(\rho_n) \cdot v(x_n) \tag{2.4}$$

Where $v(x_n)$ is the value function of the possible outcomes X_n defined as follows:

[2] In Tversky and Kahneman (1981) example, the information was presented in terms of saved lives -gains- or deaths -losses-.

$$v(x_n) = \begin{cases} (x_n - R_i)^{1-\beta} & \text{if} \quad x_n \geq R_i \\ -\lambda \cdot (R_i - x_n)^{1-\beta} & \text{for} \quad x_n < R_i \end{cases} \tag{2.5}$$

Notice that Equation 2.5 incorporates the value of gains and losses differently, relative to a subjective reference point R_i for individual i.

In Equation 2.4, x_n represents the possible outcomes of the prospect L_k. Notice that the values of these outcomes are expressed in terms of the individual's subjective evaluation $v(x_n)$, which as noticed above, is determined relative to the main experiences the subject has been exposed to and their current context as captured in R_i. This will determine the reference point from which the subject will evaluate the outcome. Therefore, the value assigned to $v(x_n)$ is expected to be updated after the most recent experience is gained, modifying the reference point for future decision-making and taking into account the perceived losses or gains on the previous experience. Equation 2.5 describes the components for the value function $v(x_n)$. Here, the coefficient λ represents the level of loss aversion, with $\lambda > 1$ to represent loss-averse individuals. This loss aversion coefficient considers that negative changes (losses) relative to the reference point affect the subject more than the same amount of change in positive terms (gains). Therefore, under this theory, it is said that the value curve $v(x_n)$ is steeper in the domain of losses than in the domain of gains. β represents the level of risk aversion such that $0 \leq \beta \leq 1$. Under PT, in the domain of gains, the individual is assumed to be risk-averse. In the domain of losses, the individual is assumed to be risk-seeking.

Additionally, thanks to the property of diminishing returns that the value function has, the impact of a change diminishes with the distance from the reference point R. Therefore, losses or gains on wealth that are closer to the reference point affect the individual more than losses or gains that are further away from the reference point. However, whether the individual takes or rejects a lottery L_k depends also on the level of certainty regarding the outcome, which is known as the *Fourfold pattern*. In this case, under the domain of losses, it is assumed an individual will adopt risk-seeking behavior if they perceive a high probability of losing, opting to reject a favorable settlement. Likewise, if the individual perceives a small probability of losing, then they may adopt risk-averse behaviors given the fear of loss, accepting an unfavorable settlement. In contrast, in the domain of gains, if the individual perceives a high probability to win, they may accept a lottery adopting risk-seeking behaviors. Whereas if they perceive a low probability of winning, they may adopt risk-averse behaviors, rejecting a favorable settlement (Harbaugh et al., 2010).

Finally, $\pi(\rho_{ni})$ in Equation 2.4 represents the decision weight, which corresponds to a monotonic function, non-linear transformation, of the probability of occurrence ρ_{ni} for each outcome. It can be defined as:

$$\pi(\rho_{ni}) = exp(-(-ln(\rho_{ni}))^{\alpha}) \tag{2.6}$$

Thus, the decision weight also depends on the cumulative distribution of the gamble.

For Equation 2.6, when $\alpha < 1$, the decision-maker over-weights low probabilities and under-weights high probabilities. Between λ and α, PT allows us to differentiate risk aversion from loss aversion. When $\alpha = \lambda = 1$, the decision problem under the PT framework reduces to the EUT setup.

Finally, under this framework of PT, the decision rule of the individual for a discrete choice problem will be determined by the lottery that provides the highest subjective value. Thus, a subject will choose the prospect L_h over L_j ($L_h \succeq L_j$), with $h \neq j$ if and only if:

$$V(L_h) \geq V(L_j) \qquad \forall h \neq j \tag{2.7}$$

2.2.4 The Decision Process In the Context of Agricultural Investment

Farmers are exposed every year to the problem of deciding their practices for the following crop season, without knowing what the weather conditions will be. One of the most important decisions they face is what type of seed input to cultivate on their working land.

A low willingness to adopt new technologies among farmers, like improved seed varieties and index insurance, has been proposed as a limiting factor in farmers' ability to mitigate the effect that climate change has on their crops and yield (Takahashi et al., 2020). From the researcher's perspective, we may count on the data that give us information regarding the outcomes that could be obtained under different weather events. Indeed, for the researchers, these outcomes may be known, and information on the objective probability of occurrence of those events could be also determined by information on past weather realizations. However, for the farmer, who has to decide before every crop season what inputs to implement, this information is unknown, facing the decision under an uncertain environment. They have to make their best guess to determine the subjective probabilities and outcomes based on their beliefs. Furthermore, there may be heterogeneity in their beliefs on the outcome and probabilities of each prospect, depending on their own experiences, being a subjective construction.

Under this context, the evaluation of a prospect (see Equations 2.1 and 2.4) will be conditional on factors that I analyze as decision drivers. Figure 2.1 shows the parameters that drive farmers' behavior under the scenario I propose here. I will assume that some of the parameters are specific to individuals, such as their probability weighting function, their level of risk aversion, and their level of loss aversion. I also assume that parameters related to farmers' beliefs about possible outcomes and subjective probabilities are directly modified by the farmer's previous experiences, which I capture in Z_i. A farmer's previous experience might include their technical knowledge related to the input; their own recent weather and input use experiences, or the recent weather and input use experiences of their peers. Additionally, more recent experiences might be expected to weigh the most in current decisions. These differences in experiences drive, in part, the heterogeneous beliefs farmers have on the value of those parameters under different weather events. Thus, the interaction between a farmer's preferences and experiences drives a farmer's decision-making process as described in Figure 2.1.

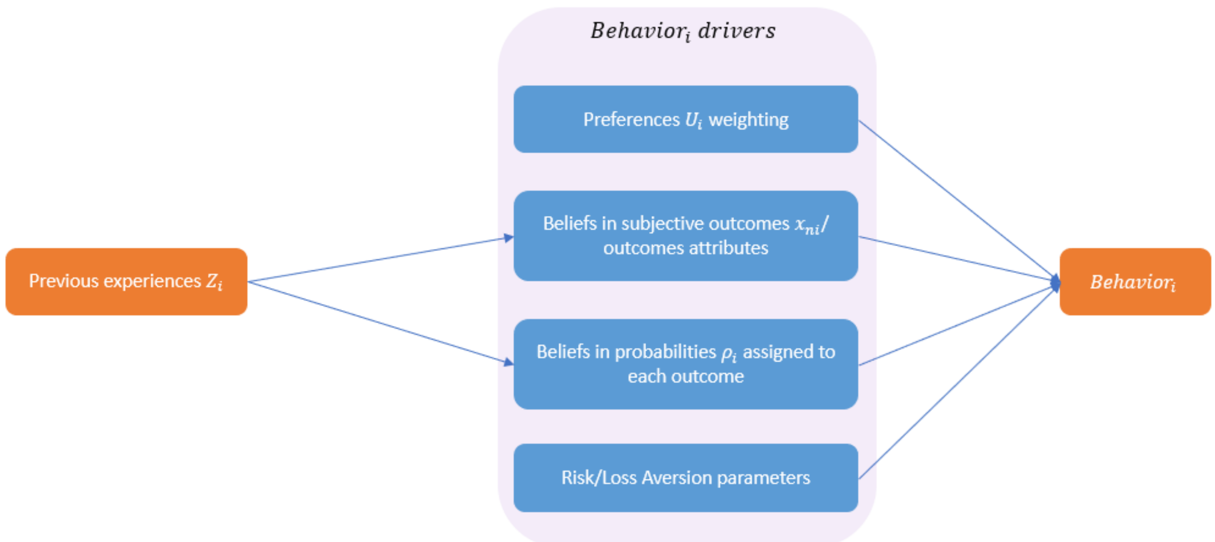


Figure 2.1: Parameters that Drive The Decision-Making Process.

Furthermore, I propose that farmers' subjective valuation of their prospects is additively separable across three domains: individual value, family value, and community value. The weights the farmers give to each of these domains are represented by Λ_I, Λ_F, and Λ_C in Equation 2.8 and their value may differ across individuals. I have the hypothesis that most of the decisions farmers make regarding what input to grow are based on their own well-being. However, I also consider that there is the possibility of nudging farmers to *activate* the other domains by calling their attention to the impact of their decisions on the well-being of others. Following this idea, the value of a prospect can be broken down as follows:

$$V(L_k) = \Lambda_I \cdot V_I(L_k) + \Lambda_F \cdot V_F(L_k) + \Lambda_C \cdot V_C(L_k) \tag{2.8}$$

Where V_I represents the individual value that a prospect brings to the farmer, V_F represents the value that the farmer may perceive through the impact of their decision on their family, and V_C represents the value the farmer may have through the impact of their decision on their community. Λ represents the subjective weights farmers give to each of these domains based on the importance they assign to the individual, family, and community well-being in their valuation of a prospect.

In order to take into account this new valuation, I will redefine the value of a prospect as [3] :

$$V(L_k) = \sum_{D} \Lambda_d \cdot \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_d(x_{ni}), \qquad n = 1, ..., n \tag{2.9}$$

Notice that the contribution of each domain to the overall subjective valuation of a prospect may vary by v_d and Λ_d. Additionally, the general setting in Equation 2.9 is compatible under both, the EUT and PT presented. Thus, the mechanisms through which farmers under this context may make a decision will be based on Equation 2.9, where the values for the probabilities $\pi_{ni}(\rho_{ni})$ and the valuation of possible outcomes v_d could be set as follows:

- If the farmer makes the decision under the framework of EUT, then they will evaluate $v_d(\cdot)$ as defined in Equation 2.2 and $\pi_{ni}(\rho_{ni})$ will represent the subjective probabilities of occurrence as defined for Equation 2.1.

- If the farmer makes the decision under the framework of the PT, then they will evaluate $v_d(\cdot)$ as defined in Equation 2.5 and $\pi_{ni}(\rho_{ni})$ will be the weighted probabilities as defined for Equation 2.6.

Finally, under either of those scenarios, the decision rule will be driven by the prospect that maximizes the value to the farmer, as defined for Equation 2.3 under the EUT or for Equation 2.7 under PT framework. Replacing 2.9 in each of those decision rules respectively, we obtain:

[3] I decided to take Equation 2.4 since it represents the more general setup for the valuation of a prospect. Notice that when $\alpha = \lambda = 1$, the decision problem under the PT framework reduces to the EUT setup.

- Decision rule from EUT: The individual will choose the prospect L_h over L_j $\forall j \neq h$ if and only if $U(L_h) \geq U(L_j)$ such as

$$\sum_D \Lambda_d \cdot \sum_{n=1}^{N} \rho_{ni}^h \cdot v_d(x_{ni}^h) \;\; > \sum_D \Lambda_d \cdot \sum_{n=1}^{N} \rho_{ni}^j \cdot v_d(x_{ni}^j) \tag{2.10}$$

- Decision rule from PT: The individual will choose the prospect L_h over L_j $\forall j \neq h$ if and only if $V(L_h) \geq V(L_j)$ such as

$$\sum_D \Lambda_d \cdot \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}^h) \cdot v_d(x_{ni}^h) \;\; > \sum_D \Lambda_d \cdot \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}^j) \cdot v_d(x_{ni}^j) \tag{2.11}$$

2.2.5 Influence of an Experimental Game in the Decision Process in the Context of Agricultural Investment

As mentioned in the Introduction of this thesis, farming activities in developing and underdeveloped regions are going to get tougher due to climate change, where the volatility of extreme weather events is going to increase. This leaves farmers with new challenges that need to be mitigated.

In the context of this research, I analyze maize farmers whose decision consists of whether to implement for the next crop season a traditional seed variety, saved from past seasons, or to adopt a drought-tolerant maize seed variety (DTM seed) and index insurance (II) that, for the purpose of the experiment, it is also assumed to be of easy to access in their market. Thus, under this scenario, I assume access to technology is given and we will focus on evaluating the next phase of whether farmers adopt the new technology.

Although new technologies like DTM seed and II can be allies in mitigating the impact of climate change on crop production, their adoption rate remains low, especially in the most vulnerable regions (Boucher et al., 2021; Carter et al., 2017; Cavane, 2016; Norton et al., 2014; Lybbert and Bell, 2010; Kostandini et al., 2009). This is why finding mechanisms through which the adoption rate can be increased is important, since the use of technologies will increase farmers' resilience to climate change (Kostandini et al., 2009; Shin et al., 2022).

Creating a simulated environment that compresses 10 years' of decisions into a day's experience may be very helpful as a learning tool for farmers that do not have information regarding the performance of improved seed varieties and II. This may help farmers to set their expected returns to a more precise estimate. Additionally, presenting to farmers a nudge that consists of a framed message that describes the benefit of the resilience-enhancing technology may nudge them to choose the new technology. These tools could be relevant for researchers and agencies that are introducing these technologies into regions where traditional practices are the dominant choice.

In this order of ideas, the intervention that the research team performed exposed the farmers to a simulated game where they will decide which type of input bundle to implement for their next crop season. Each season will randomly present a weather scenario, which could be either good weather or bad weather (implying flood or drought). Additionally, the weather can have different levels of impact, which could affect just a few households — idiosyncratic shocks — or the vast majority of the community — covariate shocks. The level of the impact will depend on the geographical location and crop inputs.

During the game, farmers will be randomly divided into three groups that differ in their exposure to a framed message intended to nudge farmers' behavior. Two of the messages will try to nudge farmers through moral suasion or socially desirable messages, where farmers are induced to think about the option that benefits their peers the most. Particularly, one of the messages focuses its attention on the benefits of the new technologies on the farmer's family and the other message focuses its attention on the benefits to both the family and the farmers' community. The remaining group will be exposed to a message that just mentions the individual benefit that adopting the new technology can bring over the farmer's maize production. Something important to keep in mind is that the game, in general, intends to nudge people towards using the bundle of improved seed and satellite index insurance by speeding up the learning process. Thus, all three groups of farmers will have this baseline nudge. The groups differ on the additional nudge they receive if any. I will discuss in more detail the design of the game in Chapter 3.

Under the scope of this research and the game, I will focus our attention to evaluate the discrete choice of the type of bundle in which a farmer decides to invest, without looking at the amount of quantity acquired. The input bundles, which represent lotteries (L_k) that the farmer will have available, are the following:

- Bundle A: Matuba seed (which represents the traditional choice)
- Bundle B: Drought tolerant maize seed (DTM seed)
- Bundle G: DTM seed plus index insurance (II)

A farmer will choose the prospect that provides them with the highest value. For the particular context of this game, the outcome x_{ni} from Equation 2.4 can be expanded to fit the particular production system, inputs, and costs associated with the game. Let:

$$x_{ni}^{k} = E - FC_k + P \cdot (f_i^k(e_n) - HH_{food}) - FC_{hh} + II_{kn}$$

Here E represents the individual's resources available, let's call it income, that allows the agent to access the options available in the choice set. FC_k represents the input fixed cost which varies by the bundle. Since I will focus on the discrete choice of the bundle, the quantities for each bundle were fixed for the game. I assume $E \geq FC_k \ \forall k$ so that all farmers have access to all the bundles. P represents the market price for the output. f_i^k represents the production function associated with each farmer that produces the outputs x depending on the input choice L_k and exogenous conditions e that depend on the weather. HH_{food} represents the production that farmers allocate to their own consumption. FC_{hh} represents the fixed cost that the farmer has to cover for other living expenses. II

represents the payment a farmer could receive by Index Insurance. The payment of the II will depend on whether the farmer has chosen Bundle C, which is the only bundle that will pay the II if a severe weather event that affects the whole community on average happens.

The general setting to evaluate each prospect defined in Equation 2.9 can then be adapted as follows:

$$V(L_k) = \sum_{D} \Lambda_d \cdot \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_d(E - FC_k + P \cdot (f_i^{L_k}(e_n) - HH_{food}) - FC_{hh} + II_{kn}) \tag{2.12}$$

The value that a farmer will expect from each bundle available during the game would be determined as follows:

$$V(A) = \sum_{D} \Lambda_d \cdot \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_d(E - FC_a + P \cdot (f_i^{A}(e_n) - HH_{food}) - FC_{hh}) \tag{2.13}$$

$$V(B) = \sum_{D} \Lambda_d \cdot \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_d(E - FC_b + P \cdot (f_i^{B}(e_n) - HH_{food}) - FC_{hh}) \tag{2.14}$$

$$V(G) = \sum_{D} \Lambda_d \cdot \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_d(E - FC_g + P \cdot (f_i^{G}(e_n) - HH_{food}) - FC_{hh} + II_n) \tag{2.15}$$

Consequently, given the problem of the farmer choosing between traditional seed, DTM seed, or DTM seed with II for their next crop season, the farmer will choose the option that brings the highest value conditional on their current beliefs.

For now, I want to clarify that just the simulated game — setting aside the framing messages — is not meant to change the level of satisfaction with the different bundles, since the subject is actually not interacting with the products per se. Instead, the game will teach farmers about the expected returns that the different bundles will have under

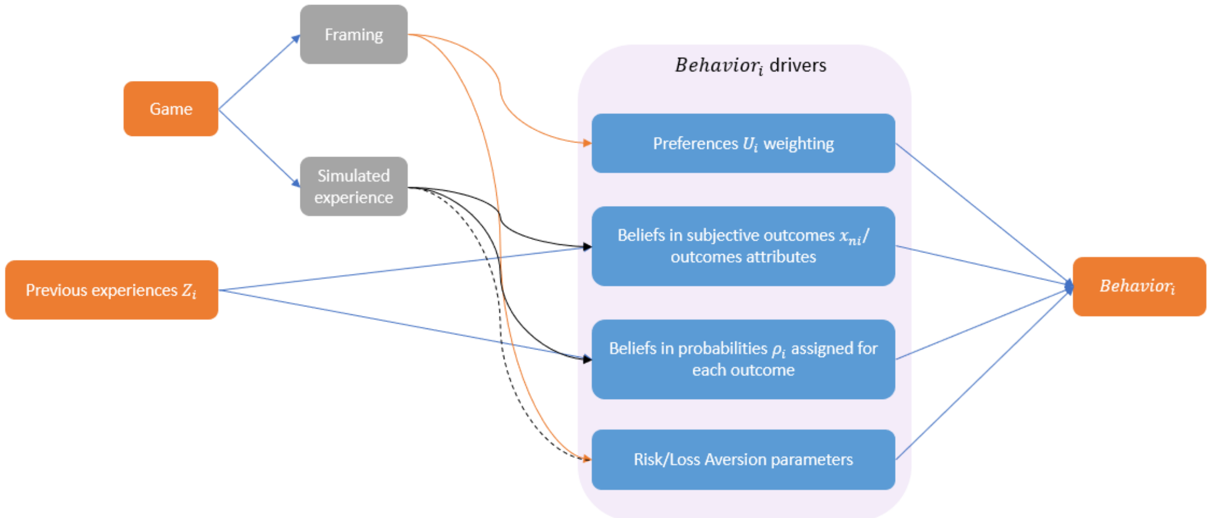


Figure 2.2: Influence of The Game on Parameters that Drive The Decision-Making Process.

different weather scenarios and the objective probability of the occurrence of weather events. Therefore, the simulated experience will not change farmers' preferences or the utility function, but help farmers learn about the probabilities ρ_{ni} and the outcomes x_{ni} more accurately. However, the framing component included during the game may generate changes in farmers' preferences as well as activate the risk aversion and loss aversion levels of the farmer. Figure 2.2 adds to Figure 2.1 the channels through which the game influences behavior. The game also affects the loss aversion parameter of the individual since the game teaches farmers how the II works. Thus, farmers may perceive sometimes that their investment in the Bundle of DTM+II represents a loss if the occurrence of a severe drought does not affect on average the community, leading to no payment. This may increase the level of loss aversion, reducing the future investment in the II bundle. However, for this research, I do not measure directly the parameters of loss aversion level, but definitely worth it to consider for future work.

Back to the valuation depicted in Equation 2.12, the impact on the decision-making of a change in the probabilities $\pi_{ni}(\rho_{ni})$ keeping everything else constant will imply that the farmer adjusted their beliefs on the probability of occurrence on the different random weather events. This may or may not alter the overall value of the bundles, since it depends on the interaction of those probabilities with the different beliefs on the returns of the bundle under those different weather scenarios. The same is true if the game modifies only the value of the returns expected under the different weather conditions keeping everything else constant. Now, when introducing the nudge, the preference for the bundles may change, even if the expected returns remind the same for all three bundles, the farmer may choose the bundle that is being incentivized by the nudge.

The nudge through the framed messages may capture the empirical observation that people also have bounded willpower and bounded self-interest. Thus, people may make choices that are not aligned with their long-run interests or are willing to sacrifice their own interests to help others (Mullainathan and Thaler, 2000). We may expect the game itself to homogenize farmers' valuation of the outcomes, given the information provided through the game. However, the framing may activate some additional subjective valuation of the outcomes, based on the value that they may bring to help others — like their family and community—. This could add again heterogeneity in the valuation of the outcomes that may depend on the degree that each individual is concerned about others.

Assume that in the absence of the framing messages, the only domain the farmer activates in their valuation of the bundles is the self-interest one. Furthermore, assume that the preferred option is the traditional bundle A in this baseline scenario and thus, $A \succ B$ and $A \succ G$. Focusing on bundles A and G, it must be the case that:

$$\begin{gathered}\Lambda_I \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_I(E - FC_A + P \cdot (f_i^A(e_n) - HH_{food}) - FC_{hh}) > \\ \Lambda_I \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_I(E - FC_G + P \cdot (f_i^G(e_n) - HH_{food}) - FC_{hh} + II_n)\end{gathered} \tag{2.16}$$

Where the same is true when comparing bundle A with bundle B. Simplifying the value functions in Equation 2.16 as $v(x_{ni}^A)$ and $v(x_{ni}^G)$ respectively, we can rewrite the condition as:

$$\Lambda_I \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_I(x_{ni}^A) - \Lambda_I \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_I(x_{ni}^G) > 0 \tag{2.17}$$

For later use, denote the left-hand side of Equation 2.17 as Γ, which we know to be greater than zero.

Now, let's assume that when introducing the framing that highlights the importance of the technology to their family, people activate the domain F, which adds the $\Lambda_F \cdot V_F(L_k)$ back to their value function. The choice between bundles A and G now depends on the sign of the inequality in the relationship depicted below:

$$\begin{aligned} &\Lambda_I \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_I(x_{ni}^A) + \Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_F(x_{ni}^A) \ \square \\ &\quad \Lambda_I \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_I(x_{ni}^G) + \Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_F(x_{ni}^G) \end{aligned} \tag{2.18}$$

If we believe that the framing can change the decision — make G preferred to A — then incorporating the family term in the equation must flip the inequality from Equation 2.16. To see the conditions under which this happens, start by assuming that:

$$\begin{aligned} &\Lambda_I \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_I(x_{ni}^A) + \Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_F(x_{ni}^A) \quad < \\ &\quad \Lambda_I \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_I(x_{ni}^G) + \Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot v_F(x_{ni}^G) \end{aligned} \tag{2.19}$$

Rearranging terms, we can identify a familiar piece from Equation 2.16:

$$\overbrace{\Lambda_I \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot \upsilon_I(x_{ni}^A) - \Lambda_I \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot \upsilon_I(x_{ni}^G)}^{\Gamma} + \Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot \upsilon_F(x_{ni}^A)$$

- $\Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot \upsilon_F(x_{ni}^G) < 0$

Making the substitution and rearranging again:

$$\Gamma + \Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot \upsilon_F(x_{ni}^A) \quad - \Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot \upsilon_F(x_{ni}^G) < 0$$

$$\Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot \upsilon_F(x_{ni}^G) - \Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot \upsilon_F(x_{ni}^A) \quad > \Gamma$$

$$\Lambda_F (\sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot \upsilon_F(x_{ni}^G) - \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot \upsilon_F(x_{ni}^A)) > \Gamma$$

$$\sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot (\upsilon_F(x_{ni}^G) - \upsilon_F(x_{ni}^A)) > \frac{\Gamma}{\Lambda_F} \tag{2.20}$$

To give some interpretation to the condition, first note that the right-hand side is positive because Γ and Λ_F are both positive by assumption. Thus, for the framing to change the decision-maker's choice, the value of prospect G in the family domain must exceed the value of prospect A in the family domain. Recall that we know the opposite was true in the individual domain. Secondly, the larger the weight on the family domain (Λ_F), the smaller the advantage of G over A in the family domain needs to be in order to flip the inequality.

There are a number of plausible explanations for the conditions described above. Notably, decision-makers may have different levels of risk and loss aversion in the family domain than in the individual domain. If large loss events are viewed as extremely undesirable in the family domain but only modestly undesirable in the individual domain, then with sufficient probability weight assigned to these states and sufficient emphasis on the family domain could satisfy the condition in Equation 2.20.

The same is true when the family and community framing message is introduced simultaneously. Following a similar reordering as before, when adding the family and community framing to Equation 2.16, the inequality could change if the following condition holds:

$$\Lambda_F \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot (v_F(x_{ni}^G) - v_F(x_{ni}^A)) + \Lambda_C \sum_{n=1}^{N} \pi_{ni}(\rho_{ni}) \cdot (v_C(x_{ni}^G) - v_C(x_{ni}^A)) > \Gamma \tag{2.21}$$

Here, the technology G, as a minimum condition, must be preferable to A in one of the two domains F or C. Once again, the more weight given to the domain in which the advantage exists, the easier it will be to overcome the advantage of A in the individual domain.

Under this context, I hypothesize:

1. Simulated experiences will affect farmers' choices by influencing their subjective beliefs about possible outcomes and their probabilities. This influence over farmers' beliefs is caused by the experience acquired while playing the simulated game.

2. Framing will affect farmers' choices by influencing preference weighting, here defined in terms of the domains of self-interest, family, and community. Farmers exposed to the family and community framed messages will have higher adoption of the resilience-enhancing technologies compared to those who were not exposed to these framed messages.

In the next section, I will test these hypotheses with the data collected by the research team during the fieldwork in Mozambique.

CHAPTER 3

THE EXPERIMENT

3.1 Introduction

Playing a game multiple times can provide a virtual experience that might alter decision-maker choices in the real world. Furthermore, certain aspects of the game may enhance its impact. In this chapter, I will first present the rationale behind the game used in the field experiment performed for this research. For this, I will review some of the approaches that have been taken to introduce games as an instrument for individual virtual learning and also review the use of field experiments to alter subjects' behaviors. Second, I will present the context of the area of study in Mozambique where the experiment was run. All the farmers participating in the study are part of communities located in Manica Province, in central Mozambique. Here, I will also present some of the demographic data collected from one of the survey instruments used by the research team during the fieldwork. Third, I will describe in detail the creation of a game that simulates farmers' experience with the environment during a growing season. Fourth, I will present a summary of the data collected from the farmers who played the game as an exploratory descriptive analysis. Fifth, I will describe my empirical approach for the game data to test the two hypotheses formulated at the end of chapter 2. To conclude the chapter, I will present the results obtained from the implementation of the empirical approach and discuss their implications for the hypotheses formulated related to the impact of the game and the framing on farmers' behavior.

3.2 Literature Review: Framed Field Experiments and Games

Field experimental design has evolved over time and the path to its present state has been explained by Levitt and List (2009) in three phases. The first phase of field experiments in the economics field can be traced back to the early 20th century when randomization was set as an important feature for field experiments in agricultural plots to study the impact of treatment effects on productivity. Later, during the second half of the 20th century, human subjects started to be used in large-scale experiments, giving life to social experiments. Governmental agencies promoted social experiments to test the impact of social interventions and inform policymakers. Finally, the third phase of field experiments surged in the first decade of the 21st century, bridging the gap between lab experiments and naturally-occurring experiments. The main types of field experiments identified under this phase are: Artefactual Field Experiments, Framed Field Experiments, and Natural Field Experiments (Harrison and List, 2004). The experiment developed for this thesis can be classified as a Framed Field Experiment. As such, I will primarily focus on Framed Field Experiments in this section.

Framed Field Experiments (FFE) are experiments tested with subjects from the population of interest, in our case, farmers. Conducting experiments directly with the population of interest allows the experiments to have a higher level of external validity compared to experiments running with "standard subjects" — usually students or volunteers (Harrison and List, 2004). This type of experiment is still under the umbrella of controlled data but it approximates the most naturally-occurring data by including important elements of the real context. FFE has been used in social experiments where the subjects of study are aware that they are part of a randomized study. Recently, the use of FFE has been extended to test theories in short periods of time, avoiding issues like attrition bias and hidden incentives common in other social experiments (Levitt and List, 2009).

The use of field experiments and games to study farmer behaviors has also become more popular in the last couple of decades (Hernandez-Aguilera et al., 2020; Viceisza, 2016). Most recent games implemented to understand farmers' behaviors can be classified into four areas: 1. Coordination and cooperation games; 2. Market games and simulations; 3. Behavior and cognitive bias games; 4. And social preference games. The first one has increased in popularity during the last years as well as topics that connect environmental issues with agriculture (Hernandez-Aguilera et al., 2020). Below I will describe some of the research that has been done regarding each of these topics.

3.2.1 Coordination and Cooperation Games

In coordination and cooperation games subjects are driven to make decisions that contribute to a common good in order to receive a reward and are encouraged to act as a group, respectively.

Tsusaka et al. (2015) performed the dictator and public good games with rice farmers in irrigated and non-irrigated areas in the Philippines. They found that farmers have more altruism and cooperation aptitudes when they share strong social ties with their neighbors, and also that social norms influence their behaviors. There is some level of interdependence that is generated when sharing social proximity within a community, and this may help us to be more willing to cooperate, perhaps to avoid feeling excluded or just because acting as a group is the easiest and fastest decision to make. This interdependence can be higher within groups inside the community, where those groups share a pool of resources or social space. In some way, sharing management practices in their daily lives in a group —intense collective actions— helps farmers develop a sense of community and caring.

The research developed by Tsusaka et al. (2015) goes a step further in their game to identify if there is any sense of shame or regret when farmers can send messages to others complaining about their little contribution to a common pool. They found that these messages influence farmers' behavior to contribute more and reduce the amount of free riders in the group. These results give us an interesting insight that people may act differently when they are being observed by their community.

Similarly, when environmental uncertainty is reduced among a group of farmers by combining self-monitoring information from their harvesting, farmers' selfish behaviors are reduced. Marrocoli et al. (2018) show this through a lab-in-the-field common pool resource experiment about bushmeat hunting with farmers in the Republic of Congo. Conversely, other research suggests that lab-in-the-field experiments that try to understand cooperation behaviors should be treaty carefully since there is an unclear relationship between behaviors under experiment-controlled conditions versus real life since social context may influence results (Torres-Guevara and Schlüter, 2016).

3.2.2 Market Games and Simulations

Market games try to mimic any conditions of a real market in order to allow players to learn about these market conditions. Similarly, simulation games simulate real-world scenarios allowing the inclusion of adequate contextual characteristics where subjects learn about decision-making and problem-solving.

This type of games play an important role to understand farmers' behaviors, through which researchers have found that framing matters, and thus, farmers can react differently under an uncertain or certain reward or punishment, keeping their expected income constant. Moser and Mußhoff (2016) confirmed this through a framed field experiment that implemented a business simulation game with a palm oil community in Indonesia where they reward or punish the reduction of intensive fertilizer use in palm oil production, finding that high rewards with low probabilities were the most effective incentive. Other studies in the market context have found that farmers prefer to take risk management options that have high-frequency payouts and insurance, as Norton et al. (2014) show through the implementation of an experimental game with smallholder farmers in Ethiopia, where participant allocated their resources among different risk management options.

However, the preference for insurance is conditional to the level of knowledge that the farmer has about the insurance, where a higher knowledge makes it more likely for the farmer to take it. Patt et al. (2010) found this result while implementing a simulation game with small-holder farmers in Ethiopia and Malawi that was meant to provide farmers with experience of a functioning insurance market to help them understand how insurance work. This gives us an important insight that teaching farmers the insurance utility and functionality through a simulated game can bring significant benefits to the well-being of the farmers' community. It should be considered in programs that want to introduce in a community best practices to mitigate farming risks.

3.2.3 Behavior and Cognitive Bias Games

Behavior and cognitive bias games tend to focus on games that measure risk preferences and attitudes. The former has suggested that preferences revealed through the game tend to align with real-world risk preferences (Hernandez-Aguilera et al., 2020).

Additionally, regarding the methods implemented in the field of behavior and cognitive bias games, it is important to consider that some games have experimental purposes, others have a learning goal to accelerate dialogue and others mix both together (Hernandez-Aguilera et al., 2020). Bosma et al. (2020) have a clear example of behavior and cognitive bias games where they developed a board game, tested with Vietnamese farmers, that simulates local shrimp farming to evaluate how this game contributes to farmers' knowledge, attitude, and behaviors, related to shrimp production systems, risk aversion, and environment perception. Here they mix experimental and learning purposes, not just to understand farmers' behaviors but also to nudge their future decisions through the experience farmers acquired while playing the game. This mixed purpose of a game can be very useful to accelerate the implementation of new technologies framing future decisions in a community.

However, researchers also have found that farmers are highly risk averse and thus attached to their traditional practices, similar to the endowment effect. Nevertheless, if they see a high probability of loss due to weather events, they may opt to implement new technologies, as Brick and Visser (2015) found through the implementation of games with farmers in South Africa. Therefore, this is also something important to consider in the design of the game if it is expected to change farmers' behaviors. On the one hand, in order for farmers to be more willing to implement technologies, they need to have experienced rain issues with their crops. On the other hand, farmers should know what are the pros and cons of implementing new technologies, and if one wants to nudge them to adopt, it should be clear the amount of losses they may have if an extreme weather event occurs and how the new technology can help to reduce those losses. This is when games with educational purposes can help farmers to understand the risk they have while minimizing the opportunity cost.

3.2.4 Social Preference Games

Finally, social preference games tend to focus on measuring trust. In this area, researchers have found that social preference games are also important in explaining farmers' behaviors. Particularly, connections within a community and trust influence positively pro-social behaviors. It is clear that reciprocity effects have allowed farmers to help each other during shocks and having connections with each other is crucial to develop these mutual aid behaviors. Some experiments that have been studied in this field show that farmers who have expend more time in a community tend to give more to their fellows compare to farmers that were recently resettled in that community, as found by Gobien and Vollan (2016). They study solidarity behaviors in established and newly resettled communities through the development of a lab-in-the-field experiment in Cambodian villages, where participants played a *solidarity game*. Their results suggest that having a long-established connection with one's community can help in the face of adverse events due to more collaboration.

Additionally, some studies have tried to capture the network effects on choice architecture through a learning process. Researchers have found that farmers' decision to adopt new technologies not only depend on their own experiences with the technology but also on the experiences that their neighbors have with these technologies. In this sense, farmers' behaviors are shaped by the idea of learning by doing but also by learning from others (Foster and Rosenzweig, 1995). One could think that farmers that have not yet experienced by their own the use of the new technologies may take into consideration the experiences of their fellows with a higher weight in the decision-making process than farmers who have their own experiences. Furthermore, the learning spillover may be influenced by who is the source of information. The credibility and trust that farmers give to their neighbors seem to matter.

Some studies show that farmers are more convinced to take into account information that came from sources with who they share group identities or similar agricultural conditions (BenYishay and Mobarak, 2019). A clear example of the above is the study developed by Leonard and Vasilaky (2016) with cotton farmers in Uganda where they performed a two-armed randomized controlled trial (RCT) to compare a traditional agricultural training program with a social network intervention with women farmers only. They found that in order to increase profitability in women farmers with low yields, it is more effective to connect them with other women farmers that have high yields than to implement traditional training where men and women are mixed to receive information. The common gender identity may play in favor to trust better the information. In contrast, other studies have found that social identity is not necessarily the only way that farmers trust the source of information regarding better farming practices, it depends somehow on the preferences. Buck and Alwang (2011) developed an artefactual economic experiment and a randomized training intervention with farmers in Ecuador to test whether farmers' trust in the source of information conditions their decision to learn during an agricultural training. They found that farmers that trust more the technical experts learn more from them during training. In summary, one could say that trust is one of the crucial factors for learning from others and this trust can be strengthened by different social preferences.

Finally, Tjernström et al. (2021) developed a virtual farming app designed as a game with the purpose of teaching Western Kenyan farmers about the yield that could be obtained using different input combinations — of fertilizer and lime — in their maize crops. The game was calibrated to simulate each farmer's plot conditions to consider farms' heterogeneities, common in that region. The authors evaluated whether the experience with the game makes farmers learn about the inputs and thus, update their beliefs about current and new technologies and subsequently change their behaviors. They found that the virtual experience can have learning effects on farmers and significantly impact behaviors.

The experimental game developed for this thesis builds on this type of gamification approach that simulates real context features that allow farmers to experience more than one outcome in a short period of time. The results in this thesis will contribute to the understanding of the utility that virtual learning platforms in the field can have when introducing new technologies in a small-holder agricultural context. In this thesis, I will test the learning effects of a virtual game in the context of small-scale farmers in Mozambique to teach farmers about drought-tolerant technologies and index insurance. This method may increase the engagement of farmers with the information received, promoting exploration and discovery due to the low opportunity cost. Although, in addition, I will randomize different versions of the game to determine whether framing messages can intensify the impact that the virtual experience can have on farmers' beliefs and behaviors.

3.3 Experimental Game Design

The game developed for this research simulates farmers' experience when growing maize. It is a controlled Framed Field Experiment where the environment of the game is adapted to the naturally-occurring context of farmers in Manica province, Mozambique. Before starting the game, enumerators were assigned to visit the farmers and complete a survey at their homes to collect farmers' data, including information about the household members, the respondent completing the survey (where 81% of them are the household heads), and farm features and practices. After completing the survey, some of the farmers were randomly assigned to participate in the virtual maize farming game. Around 24.8% of the farmers participating in the survey completed the game, with a total of 275 farmers. The game is meant to change behavior in the sample group as the rounds of the game progress, due to the virtual experience gained over time during the game. All subjects were informed that their participation in the research was voluntary, they could skip or leave at any time, and that their responses were being recorded. [1]

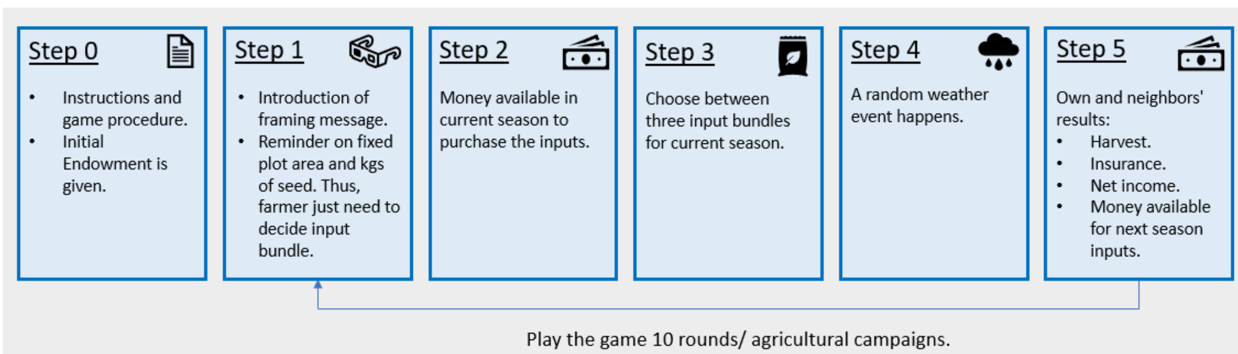


Figure 3.1: Summarized Game Procedure.

Figure 3.1 describes the game procedure, where each participant plays 10 rounds, each representing an agricultural campaign. To start (step 0) the participants were informed about the resources they will have available during the game. Since the goal is to understand farmers' input decision process. Other factors that could make the decision more complex were left as fixed. Thus, each farmer was set to manage one hectare of maize, using 25 kilograms (kg) of maize seed in every season presented by the game. Farmers only need to decide for each season the type of input bundle they want to select. The input decision in one season can be changed from season to season. Thus, farmers could maintain or change their decision at any point during the ten rounds of the game.

[1] See consent note in Appendix A.

Farmers were also instructed to manage the plot as they would in real life. Thus, it is assumed farmers will use their subjective probabilities of weather occurrence and outcomes and make the decision based on their preferences.

The input bundles available in each round and their associated cost are shown in Table 3.1. Here, bundle A represents the traditional technology farmers normally use and is the cheapest option available. Bundle B and bundle G represent the resilient-enhancing technologies, where DTM seed is a variety of seeds resistant to mild drought events and the satellite-based index insurance is a complement farmers can acquire to insure their crops in the face of severe droughts.

Table 3.1: Input Bundles Available and Their Associated Cost.

Input bundle	Total cost	Cost per Kg
Bundle A: Traditional seed (Matuba) (25 kgs)	\$2,500 MT (∼ USD\$39.5)	\$100 MT (∼ USD\$1.58)
Bundle B: Drought Tolerant Maize (DTM) seed (25 kgs)	\$4,000 MT (∼ USD\$63.25)	\$160 MT (∼ USD\$2.53)
Bundle G: DTM seed (25 kgs) + Satellite-based Index Insurance (II)	\$4,250 MT (∼ USD\$67.2)	\$170 MT (∼ USD\$2.69)

The game is set to have four different levels of rainfall that a farmer could experience. Additionally, there is some chance that the weather experienced by the farmer differs from the weather experienced by the community at large, particularly for drought events. This feature is included to allow farmers to learn about the concept of basis risk, which is inherent to index insurance products and is known to discourage uptake. The probability of occurrence of the various weather events was calibrated with data on rainfall from Manica Province in Mozambique during the period 2015-2019. Table 3.2 shows the probability of occurrence of each possible combination of weather events during the game, at the individual and community levels. Figure 3.2 shows the images farmers saw during the game for each of the possible weather occurrences.

Table 3.2: Probability of Weather Experience During The Game.

Community experience	Individual experience	Probability
Good weather	Good weather	(0, 0.4)
Severe drought	Severe drought	[0.4, 0.49)
Mild drought	Severe drought	[0.49, 0.5)
Mild drought	Mild drought	[0.5, 0.9)
Flood	Flood	[0.9, 1)

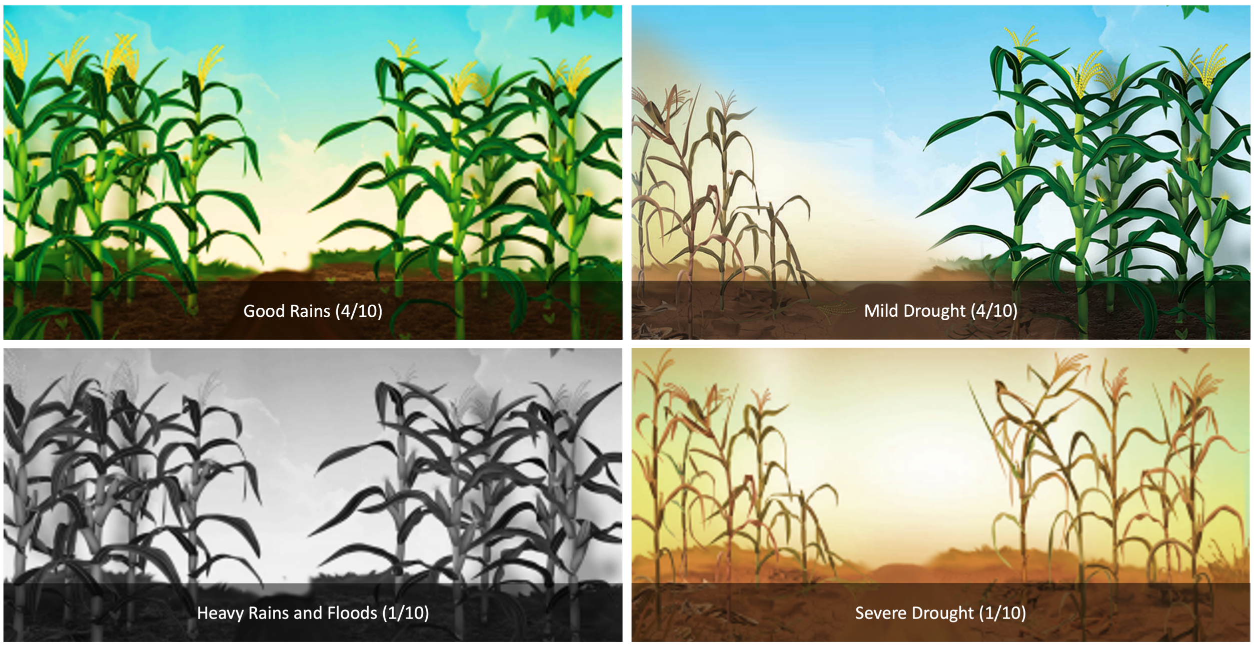


Figure 3.2: Weather Card Presented to Farmers During The Game.

To access any of the three bundles in the first round, each farmer received an endowment within the game of \$10,000 MT ($\sim$ \$158). The harvest for each season will vary depending on the weather conditions during the season and the type of seed used in the plot. Table 3.3 describes the outcomes associated with the Matuba seed and the DTM seed under each of the four types of rainfall. As it shows, the DTM seed outperforms under mild drought (little rainfall) and good weather (regular rainfall). The exact yields associated with each weather event and input bundle are unknown to the farmer at the beginning of the game. Farmers discover the performance of their chosen inputs and the probabilities of the different rainfall events while playing the game, letting them reset their subjective expectations and, if they wish, change their input decision.

Table 3.3: Kilograms (Kgs) of Maize Harvested Under Each Type of Seed and Weather.

Weather	Outcome by Matuba input (in Kgs)	Outcome by DTM input (in Kgs)
Good weather	2,000	4,500
Severe drought	1,500	4,000
Mild drought	700	1,500
Flood	700	1,500

In addition to learning about the seeds' performance, the game offers an opportunity to learn about index insurance. The insurance included in bundle G is designed to mimic a product available through local agro-input dealers. The product makes an indemnity payment equal to \$1,600 MT ($\sim$ USD\$25.3) if the community experiences a severe drought (covariate drought). Thus, if an idiosyncratic shock happens, the farmer who has selected bundle G and has been affected by a severe drought will not receive the insurance payment. In this case, the farmer will experience an extra cost derived from the payment of the premium, besides the losses caused by the shock.

After farmers are given the instructions for the game and the endowment, they start playing the game (step 1 in Figure 3.1). The game has three versions that differ by the type of framing message the farmer is exposed to during the game. Each farmer is randomly assigned to one of the three treatment groups, where the probability of being assigned to each of the treatments is equally distributed. The three versions of the game were developed to study if slight variations in the way in which the game is presented produce different results in farmers' input decisions, particularly whenever framing messages of moral suasion are introduced. These framing messages are meant to make the farmer think about the value that a given prospect could bring to themselves, their family, and/or their community. The framing messages are:

- **Framing1**: *Drought-tolerant maize seed varieties and insurance can help mitigate the impact of bad weather conditions on maize production.*

- **Framing2**: *Drought-tolerant maize seed varieties and insurance can help mitigate the impact of bad weather conditions on maize production. Mitigating the impact that bad weather conditions can have on your production is an important part of sustaining your livelihood and the well-being of your household members and your community.*
- **Framing3**: *Drought-tolerant maize seed varieties and insurance can help mitigate the impact of bad weather conditions on maize production. Mitigating the impact that bad weather conditions can have on your production is necessary to sustain the livelihood of your household members.*

Figure 3.3: Image Shown to Farmers When The Framing Message Was Presented.

Figure 3.3 was presented to farmers during the experiment whenever they were reading the framing message.

Notice that Framing 1 puts emphasis on the benefits that bundle G will bring just to the farmer as a risk-reducing strategy. The benefits are presented in terms of their maize yield, giving value to this bundle for the higher monetary return the farmer may obtain under unfavorable weather conditions, like a severe drought season. On the other hand, Framing 2 and Framing 3 also mention the individual benefits of bundle G in terms of yield but in addition, they nudge farmers to think about the benefits that this bundle may bring to the livelihood and well-being of their household-and-community members and to their household itself, respectively. Thus, as explained in Chapter 2, the exposure of farmers to Framing 2 and Framing 3 may activate their family and community domains in the valuation of a bundle, where farmers may give additional value to Bundle G depending in part on the level of engagement they have with their family and community.

After farmers see the framing, they are told to remember that they have a fixed plot of one hectare and a fixed amount of seed input to buy — 25 kgs — and that they just need to decide which bundle to purchase. Then, in step 2, the farmer is told about the money they have currently available to do the purchase of one of the bundles. This money available will be automatically updated after each round of the game is played. The income E for each round $t \in [1;10]$ can be formalized as follows:

$$E_t = \begin{cases} \$10,000MT & \text{if} \quad t = 1 \\ E_{t-1} - FC_k + P \cdot (f_i^k(e_n) - HH_{food}) - FC_{hh} + II_{kn} & \text{if} \quad t > 1 \end{cases}$$

In the first round (t=1), the farmer will have the endowment given at the beginning of the session. From round two and forward, the income the farmer will end up with will be determined by the income with which they started the round (E_{t-1}), plus the revenues earned from their maize plot, minus the cost incurred to purchase inputs and maintain their household. It is important to notice that the harvest for the season, $f_i^k(e_n)$, will depend on the random weather conditions e_n with $n \in [1;4]$ representing the four possible types of rainfall levels and the type of seed used (see Table 3.3). Since the game is trying to be as realistic as possible, 300 kgs of the harvest need to be set aside for household consumption, represented by HH_{food}. Then, the harvest that is left will be sold in the market for a fixed price P (\$10 MT per kilogram of maize). Part of the income that comes from this sale will be used to cover \$5,000 MT fixed household expenses, represented by

FC_{hh}. The cost of the input bundle chosen, FC_k, is also subtracted. The rest of the income from the sale will be added to the income, E_t, available for the next season. Finally, the farmers who chose Bundle G are eligible to receive indemnity from the insurance if the community is affected by a severe drought. In this case, the insurance pays \$1,600 MT ($\sim$ USD\$25.3) which also will be added to the budget available for the following season.

After the farmer is informed about their available budget, they move to step three of the game where they will make a decision about what input bundle to choose for the current season (see Table 3.1 for information on the bundles available). Farmers do not have advance information about what the weather draw will be, it is unknown at this point of the game. Thus, I assume farmers will make the best decision based on their subjective weather probabilities. After the decision is made, farmers will move to step four of the game, where a random draw happens and defines the weather conditions the farmer and the community will experience during that season (see Table 3.2 for information on the possible combination of weather events at the individual and community level and Figure 3.2 for a visualization of how farmers saw the weather event). Finally, in step 5 of the game, the farmer will see the results for that round of the game. The game will inform the farmer about the harvest obtained in that season given their input choice and the weather conditions. It will also inform the farmer whether they receive a payment from the insurance II_{kn}, as well as their net income that will be available for the next season (namely, E_t when $t > 1$).

Importantly, the results screen will also show the farmer how he performs compared to two of his neighbors: Aniceto and Felipa. [2] Aniceto will always purchase Matuba and Felipa will always purchase DTM seed with II. The goal for having the performance of the farmer's neighbors at the end of each round is for the farmer to be able to compare the results of their decision with the result they could have obtained if they have chosen the

[2]Both characters are created with an educational purpose. They are not real people making decisions during the game.

other type of seed and insurance. Thus, if the farmer chooses Bundle A, then in the results screen they would be able to see what their results could have been if they have used the DTM seed input and vice versa. This adds an extra discovery piece for the farmer, which may increase their engagement and learning process during the game.

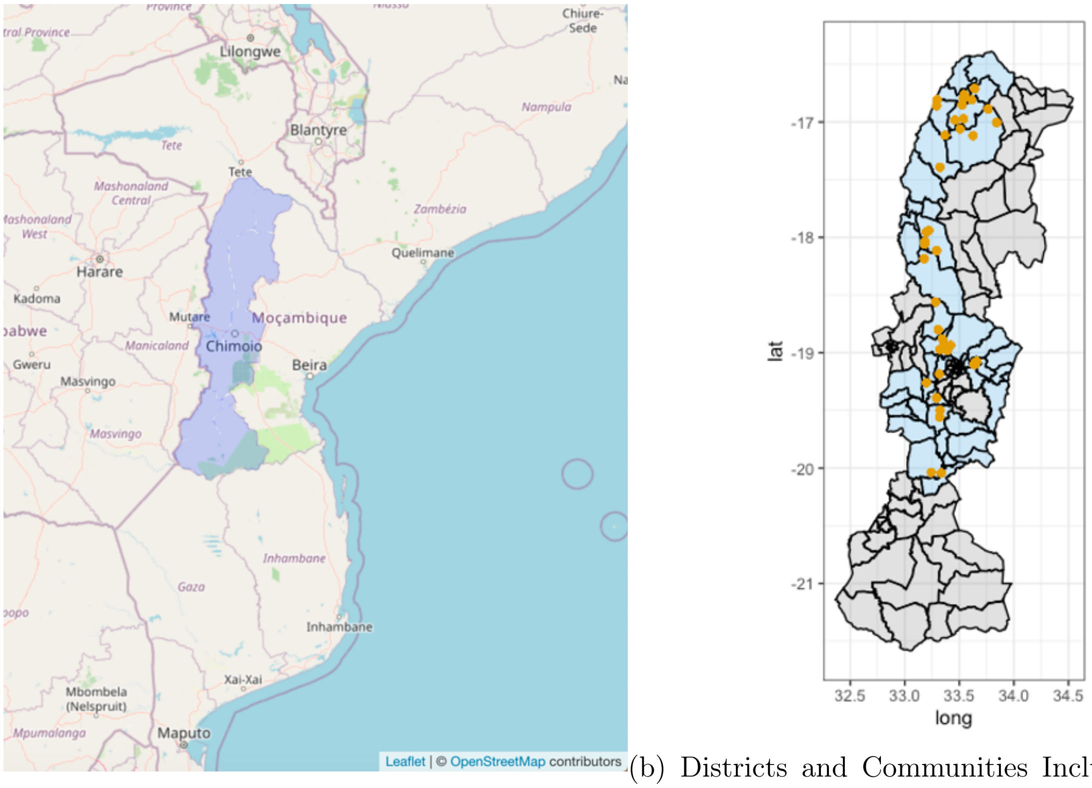
To conclude, the main function of the game is to contribute to farmers' understanding of the impact that extreme weather events can have on their yield, their household, and community livelihood and well-being, by providing a low-consequence opportunity for experimentation.

3.4 Description of the Data Collected

3.4.1 Description of the Sample: Farmers in Manica Province, Mozambique

The study area focuses on 80 villages located in 5 districts of Manica Province, Mozambique. The districts of study are: Garue, Bandola, Guro, Sussundenga, and Vanduzi. The full sample is made up of 1,107 farmers from these villages who participated in a survey that collected data about their household characteristics and agricultural activities. From this pool of subjects, 275 farmers were randomly selected to participate in the game. This sub-sample includes farmers from 40 villages distributed across the 5 districts of the study area (see Figure 3.4).

Table B.1 shows summary statistics describing the full sample that participated in the survey as well as the participants in the game. The farmers in the whole area of study have on average 1.68 plots with an average total area of 4.5 hectares. Around 66% of the managed area is cultivated with maize, one of the main staples in Mozambique, with an average yield of 613.7 kilograms of maize per hectare cultivated. Less than half of the farmers are aware of the existence of improved maize seeds marketed as drought-tolerant (DTM) (27% of the farmers) and fewer are aware of any improved maize seeds that are insured against weather risk (4.9%). This could be part of the reason why farmers in this



(a) Manica Providence, Mozambique.

(b) Districts and Communities Included in The Study

Figure 3.4: Area of Study: Manica Providence, Mozambique.

area have a low level of adoption of new technologies. Only 30.6% of the full sample used any improved maize seed in the prior agricultural season and just 10.7% used any type of DTM seed. Additionally, just 4.4% of the farmers used any inorganic fertilizer on their plots and fewer used organic fertilizers such as manure or compost (1.4%). Besides the low adoption of technologies that could improve crop yield, farmers' livelihoods are also vulnerable. On average, farmers in the sample have a 33% probability of being below the National Poverty Line and 44.2% of them are food insecure. The sample for the game looks very similar to the full sample, although the percentage of farmers aware of improved maize seeds that come with insurance drops to 2.6%.

The mix of high agricultural dependency, low technological adoption, and livelihood constraints makes it important to find mechanisms that give this farmer population the tools to increase their resilience in the face of increasingly frequend rainfall failures.

Table 3.4: Summary Statistics.

Variable	(1) Full Sample	(2) Game Sample
Plots (#)	1.680	1.640
	(0.858)	(0.887)
Total Area (ha)	4.532	4.728
	(6.263)	(7.997)
Area in Maize (ha)	2.996	2.977
	(3.063)	(2.761)
Yield (kg/ha)	613.760	605.241
	(520.231)	(518.387)
Use Any Improved Maize (%)	0.306	0.305
	(0.461)	(0.461)
Use Any DTM (%)	0.107	0.084
	(0.309)	(0.277)
Use Any Inorganic Fertilizer (%)	0.044	0.062
	(0.206)	(0.241)
Use Compost/Manure (%)	0.014	0.007
	(0.116)	(0.085)
Aware of DTM (%)	0.278	0.248
	(0.448)	(0.433)
Aware of Ag. Insurance (%)	0.048	0.026
	(0.214)	(0.158)
Probability Below National Poverty Line	0.330	0.328
	(0.190)	(0.189)
Food Secure (%)	0.558	0.560
	(0.497)	(0.497)
Observations	1,107	275

Note: Standard deviation in parenthesis.

3.4.2 Descriptive Analysis of the Game Data

This section presents descriptive results from the game data. The section will provide insights into how farmers played the game. Most of the farmers selected to play the game completed all 10 assigned rounds (95% of the farmers), where each round represents an agricultural campaign.

Figure 3.5 shows the frequency of weather events per round. Weather events were randomly assigned with probabilities calibrated to historical data from the study region. The most frequent weather events during the game were mild droughts and good weather,

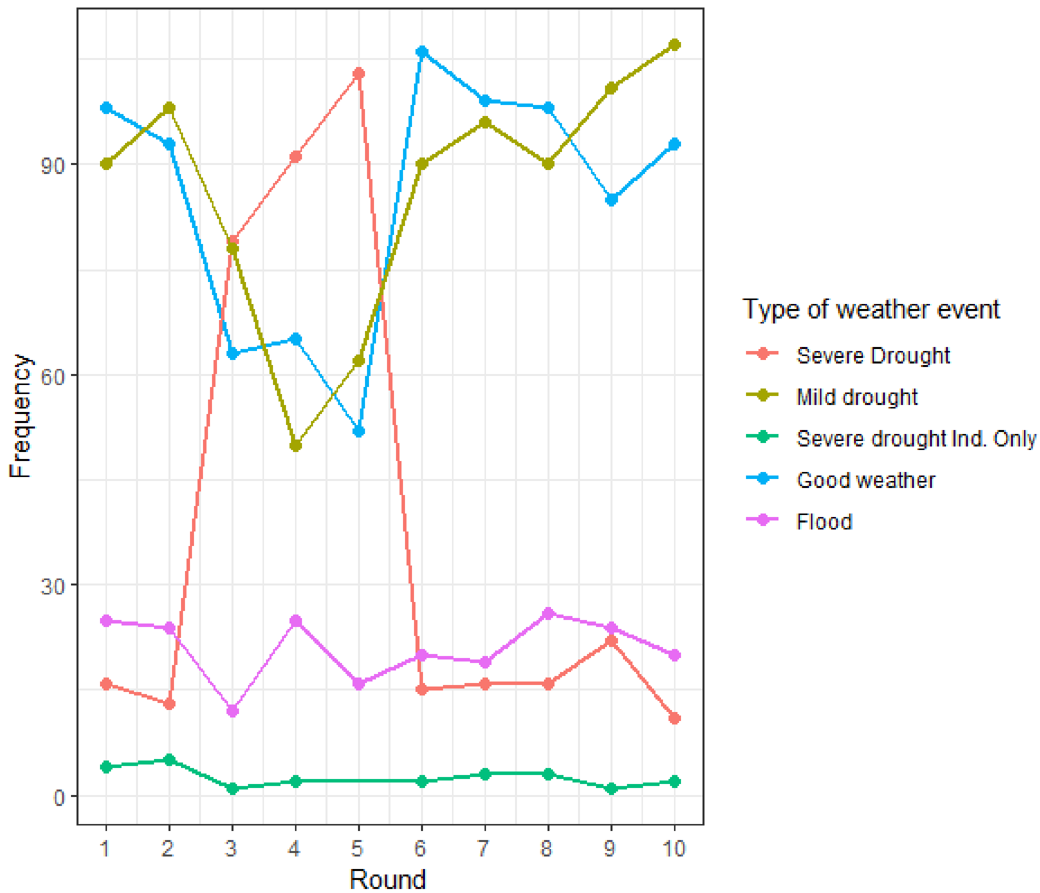


Figure 3.5: Frequency of Weather Events per Round.

representing good rainfalls for growing crops. The only deviation from the random assignment of weather events was that farmers were guaranteed to experience a severe drought sometime during the first five rounds of the game. Table 3.5 summarizes farmers' first experience with a severe drought event. As it shows, by the fifth round 100% of the farmers have experienced a drought event. This may influence the decision-making process after round 5 since all farmers will have experienced how their chosen inputs perform under drought conditions. Across the 10 rounds of the game, 84.54% of the farmers experienced between one and two drought seasons. The maximum number of rounds with droughts events experienced by a farmer was 5. As such, all farmers were able to gain experience with the performance of the inputs chosen under different weather conditions (see Table 3.6).

Table 3.5: Round When The First Severe Drought Was Experienced.

Round	Frequency	Percentage	Cum.
1	20	8.58	8.58
2	18	7.73	16.31
3	68	29.18	45.49
4	64	27.47	72.96
5	63	27.04	100

Table 3.6: Total Number of Rounds in Which a Severe Drought Event Was Experienced.

Number rounds with droughts	Frequency	Percentage
1	105	45.06
2	92	39.48
3	29	12.45
4	6	2.58
5	1	0.43

Figure 3.6 describes farmers' average net income for each of the 10 rounds of the game. As described in Section 3.3, Aniceto always chooses the traditional Matuba option and Felipa always chooses the DTM+II bundle. Given the bundle chosen by the farmer during each round of the game and their combination with the weather conditions, the average outcome for the farmers during the game approaches Felipa's outcome more closely than Aniceto's outcome. Between rounds 3 and 5, the farmers experienced on average their lowest net income, driven by the severe drought events experienced during those rounds as reported in Figure 3.5. The average budget available at the beginning of the season increases as the rounds progress, with net income from each season adding to the initial endowment provided to the farmer at the beginning of the game (see Figure 3.7).

Figure 3.8 presents the frequency with which each input bundle was chosen by the farmers in each round. The selection of the DTM+II bundle increases notably between rounds 3 and 5, probably in response to farmers experiencing their first severe droughts during those seasons. The DTM-II bundle is the only bundle that protects against covariate severe droughts. The frequency of farmers choosing the DTM+II stabilizes after round 5 with around 66% of the farmers choosing this option. In the last two rounds of the game, the

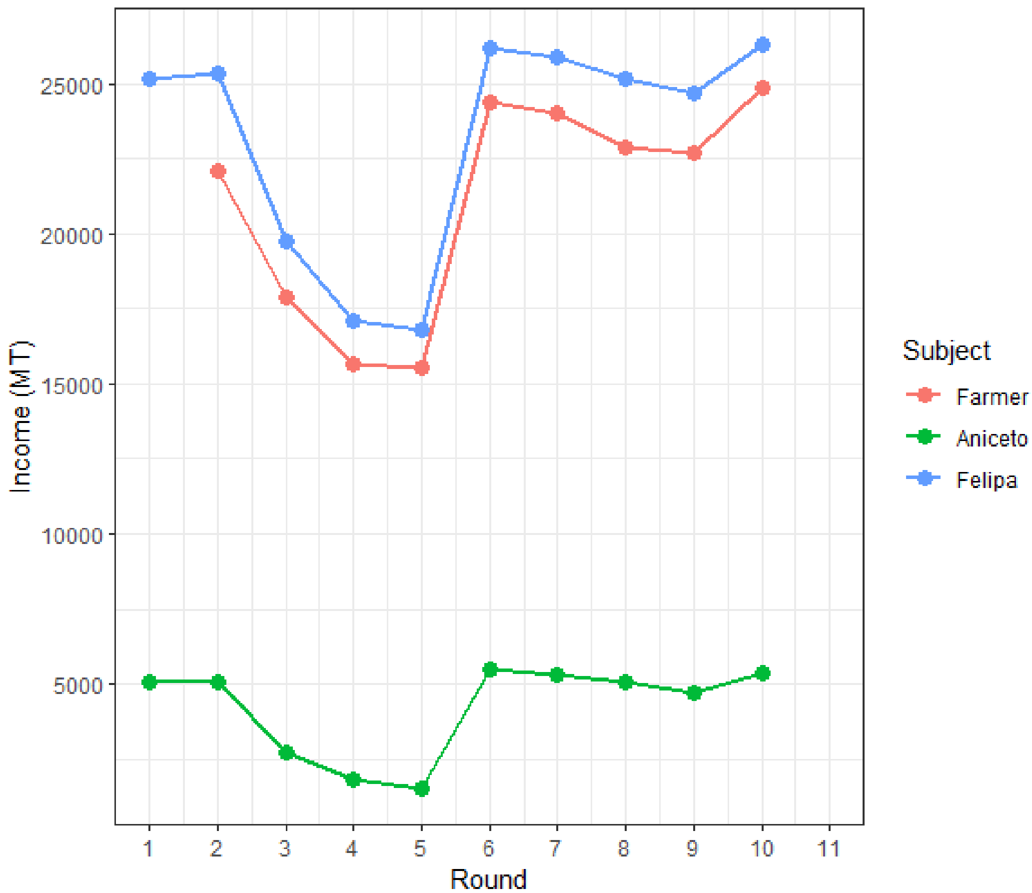


Figure 3.6: Average Net Income per Round.

use of the DTM-II bundle increases once again, reaching its highest popularity with almost 72% of the farmers adopting it. On the contrary, the frequency of farmers selecting the Matuba bundle decreases between round 1 and round 4, then stabilizes until round 9. Around 8.5% of the farmers adopt the Matuba bundle for most of the game, though it reaches its lowest popularity in the last round of the game where just 6.8% of the farmers adopt it. Selection of the DTM input bundle increases from round 1 to round 3, where it reaches its highest point at around 31% of the farmers adopting the DTM bundle. Then, its adoption decreases from round 3 to round 5, probably because this bundle does not protect against severe droughts, which was common in these seasons. From there, it stabilizes until the last round of the game, with around 23% of the farmers adopting it. Thus, in terms of the inputs chosen throughout the game, the most notable changes from

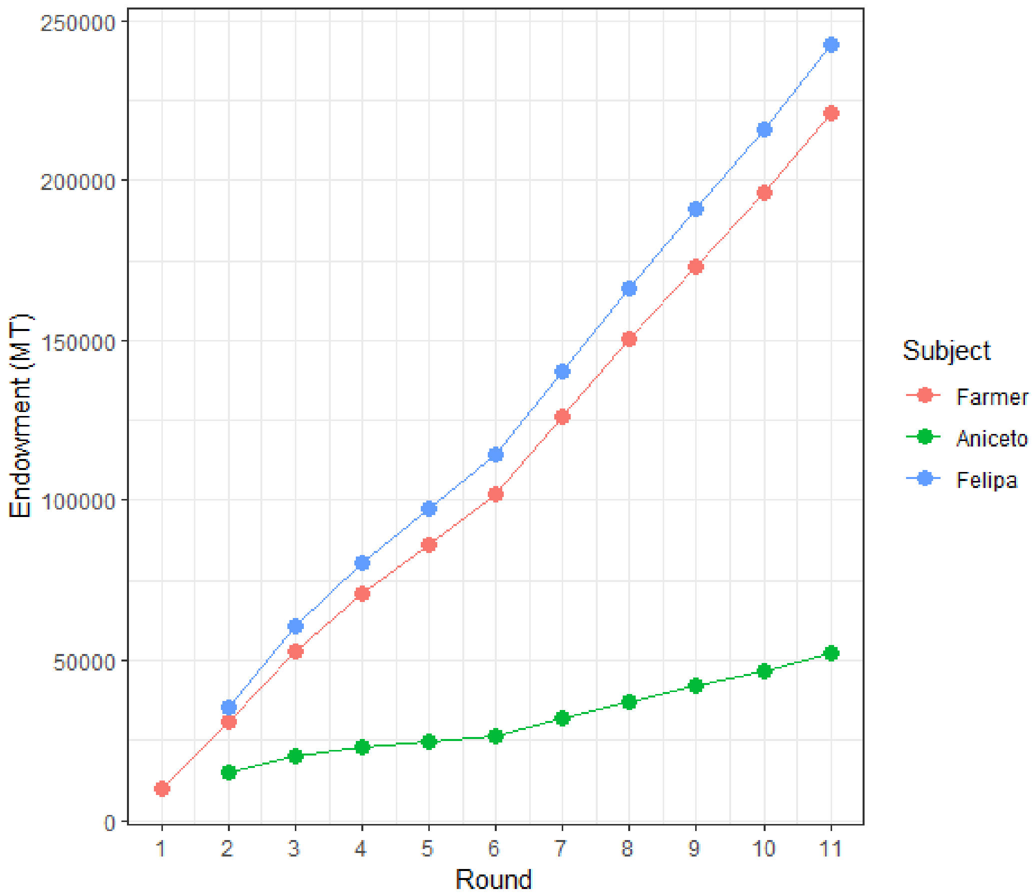


Figure 3.7: Average Endowment per Round.

the first round to the last round happened in the insured bundle — which experiences a positive change of about 13 percentage points — and in the traditional bundle — which experiences a negative change of about 14 percentage points.

Interestingly, 57% of farmers never played the traditional bundle, Matuba (see Table 3.7). This could be explained by the fact that, on the one side, 30.5% of the game sample was already using improved maize varieties in real life (see Table B.1) and, on the other side, farmers may feel more willing to experiment with new input bundles in the simulated experience since the consequences of losing during the game are not as harmful as in real life. Furthermore, Figure 3.9 shows that, in all rounds, there are farmers who directly experienced the benefits of their chosen inputs. For example, buying the DTM seeds with either bundle B or G and experiencing a mild drought season, which highlights the

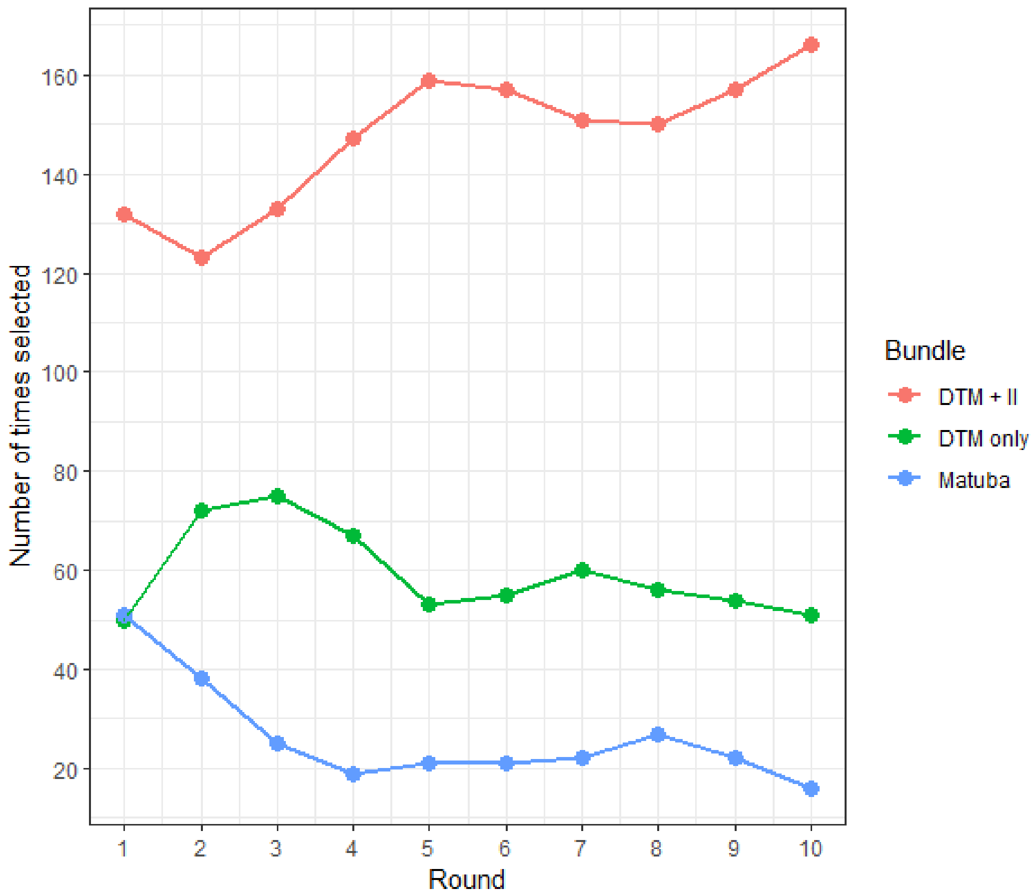


Figure 3.8: Frequency of Farmers Selecting Each Bundle Type per Round.

advantage of the DTM seed over Matuba. Similarly, buying the insurance bundle — bundle G — and receiving an indemnity payment after a severe drought shock highlights the benefits of insurance. However, for almost all rounds there are also cases where the farmers invested resources in a new technology and perceived none of its benefits, either because the weather was not ideal for the DTM seed to demonstrate its advantage or because there was not a severe drought to trigger an insurance payment. Thus, farmers may perceive that their investment in a new technology represents a loss since they did not experience the technologies' benefits which may increase farmers' loss aversion, leading them to change their behavior for future investments. Additionally, there are also cases where farmers who did not invest in the insurance bundle experienced severe drought. These last cases could generate a feeling of regret for past decisions.

Table 3.7: Number of Times a Bundle Was Selected During The Game.

Input Bundle	Never	From 1 to 3 times	From 4 to 6 times	From 7 to 9 times	Always
Bundle A: Traditional Matuba	133 (57%)	84 (36%)	10 (4%)	1 (0%)	5 (2%)
Bundle B: Drought Tolerant Maize (DTM) Seed	76 (33%)	76 (33%)	65 (28%)	7 (3%)	9 (4%)
Bundle G: DTM seed plus Index Insurance (II)	19 (8%)	36 (15%)	59 (25%)	51 (22%)	68 (29%)

The frequency of selection of the input bundles could follow different patterns depending on the version of the game that the farmers were playing. Table 3.8 shows the randomization of the game sample into the three versions of the simulated experience, which differ from one another in the type of framing to which the farmer was exposed. The randomization resulted in a sample that is well-balanced across the three versions of the game [3] . Figure 3.10 shows that the percentage of farmers choosing the insurance bundle increases after the second round under the framing that highlight the benefits of this bundle for the individual in terms of yield, family, and community livelihood and well-being. Nevertheless, the percentage that chose this bundle reduces after the fifth round for those exposed to the framing that only highlights the benefit of the bundle in terms of yield and household livelihood. In contrast, the percentage of farmers who choose the insurance bundle tends to increase until the last round for those who were exposed to the framing that also highlights the benefits that the bundle could bring to the community. This may be aligned with the importance that farmers give to their communities. In general, there is a tendency to increase in the percentage of farmers who decide to choose the Insurance bundle as the rounds of the game progress and the increase is bigger among those exposed to the community framing (Framing 2).

[3]See table B.1 in appendix B for summary statistics of each framing group and the significance in the difference in means between treatment arms using t-test.

	Round									
	1	2	3	4	5	6	7	8	9	10
DTM (Bundle B and G)										
Mid-season drought (mild)	69	86	72	48	56	80	88	81	90	104
No-mid season drought (mild)	117	112	138	169	157	134	124	128	123	115
Insurance (Bundle G)										
Payment	11	6	47	55	71	10	13	11	15	6
No payment + no severe drought	127	117	89	93	90	147	138	141	146	160
No payment + only Individual severe drought	0	2	1	2	0	2	1	1	1	1
No insurance (Bundle A and B)										
Severe drought	9	9	32	39	33	7	5	7	7	6
No severe drought	88	101	66	46	41	69	78	75	66	62

Figure 3.9: Actual and Potential Insurance Payments.

Table 3.8: Number of Farmers Randomly Assigned to Each Version of The Game.

Framing type	Frequency	Percentage
Framing 1 (Individual)	69	29.61
Framing 2 (Individual, community and HH)	74	31.76
Framing 3 (Individual and HH)	90	38.63

On the other hand, Figure 3.11 shows the percentage of farmers who choose the Matuba bundle under the different framing types. For all three groups, there is a decreasing tendency in the percentage of farmers who decide to choose the traditional Matuba bundle as the rounds of the game progress. The biggest decrease for those exposed to Framing 1 and 3 happens from round 1 to 4, and from round 1 to 5 for those exposed to the community framing. After this, the percentage of farmers choosing this bundle stays low and fluctuates around 8% of the farmers for each group.

Finally, Figure 3.12 shows the percentage of farmers selecting the DTM seed bundle under each type of framing. Here the patterns are not clear. There is a general increase in the selection of this bundle from round 1 to round 2, and there is a general decrease from round 3 to round 5, which make sense since this bundle does not protect against severe droughts, common during these rounds. After this, there is a lot of fluctuation in the

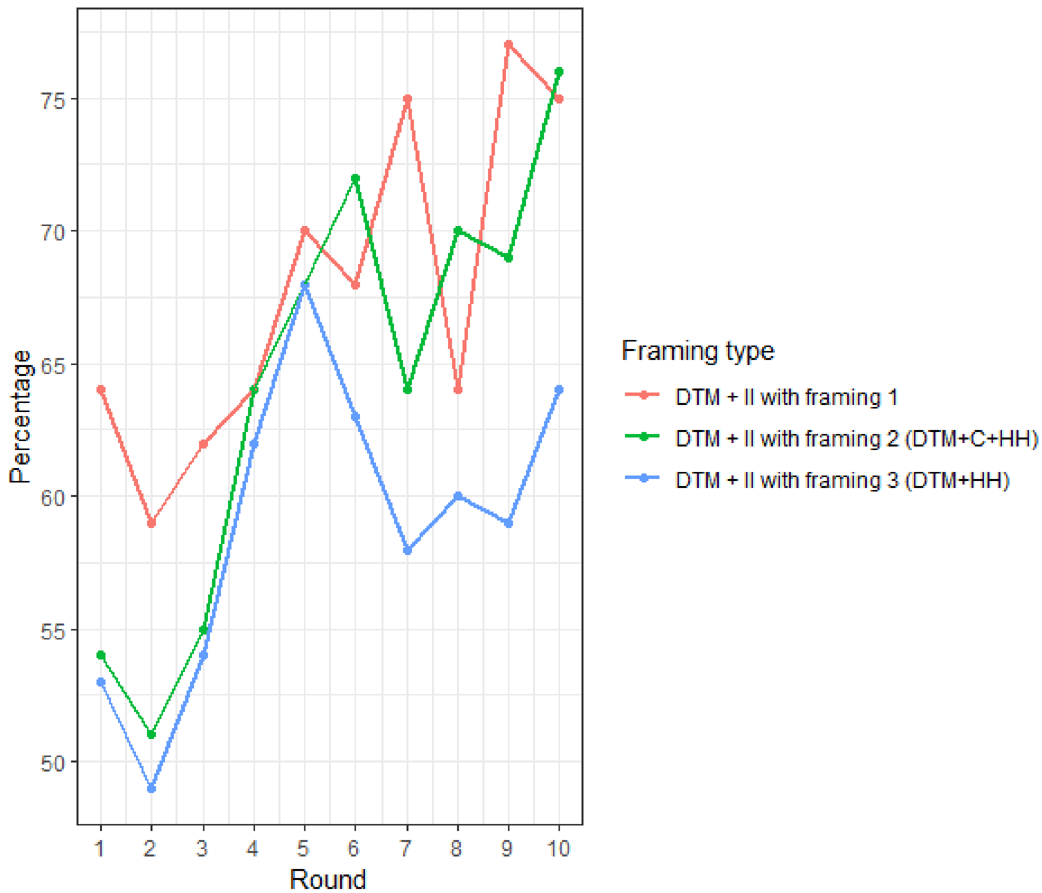


Figure 3.10: Percentage of Farmers Selecting The Insurance Bundle by Framing.

percentage of farmers selecting this bundle. Nevertheless, those exposed to Framing 3 are the ones who mostly adopt the DTM bundle. An interesting pattern is that those exposed to the community framing (Framing 2) are the ones who adopt the insured bundle the most, perhaps since the insurance pays as soon as the community as a whole is affected by a severe drought. On the other hand, the adoption of the DTM bundle is higher for those exposed to the household framing (Framing 3).

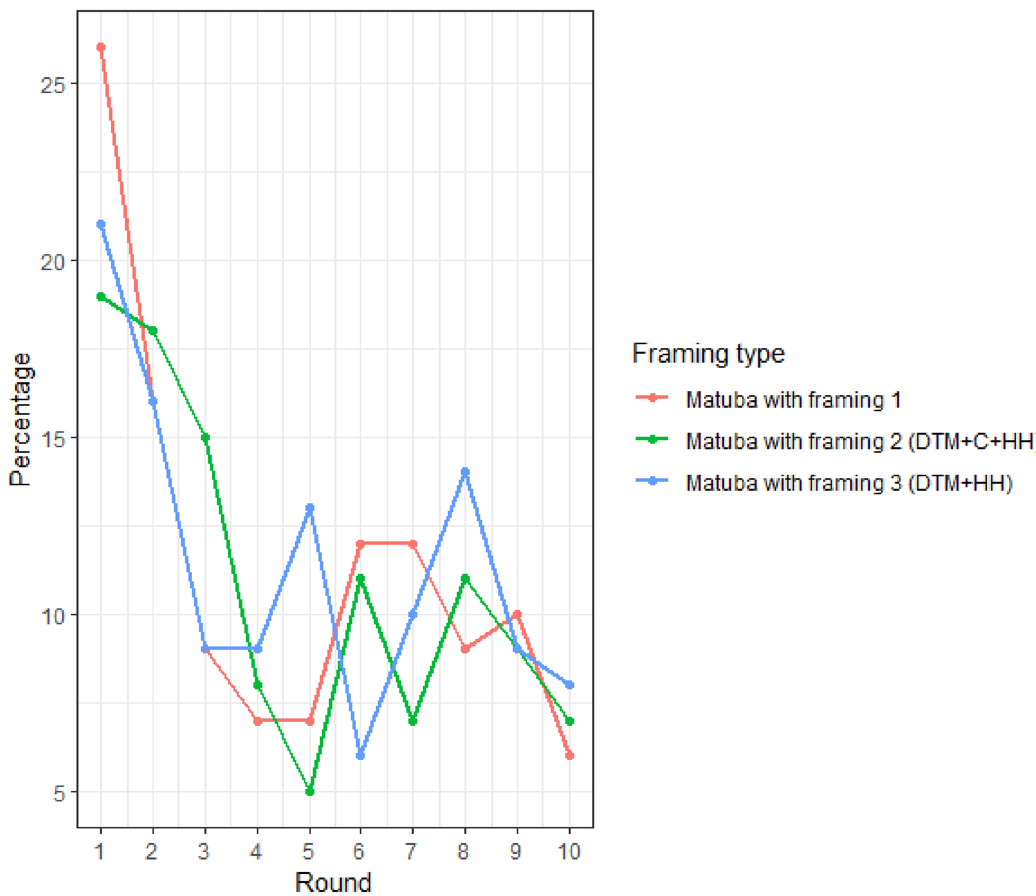


Figure 3.11: Percentage of Farmers Selecting The Matuba Bundle by Framing.

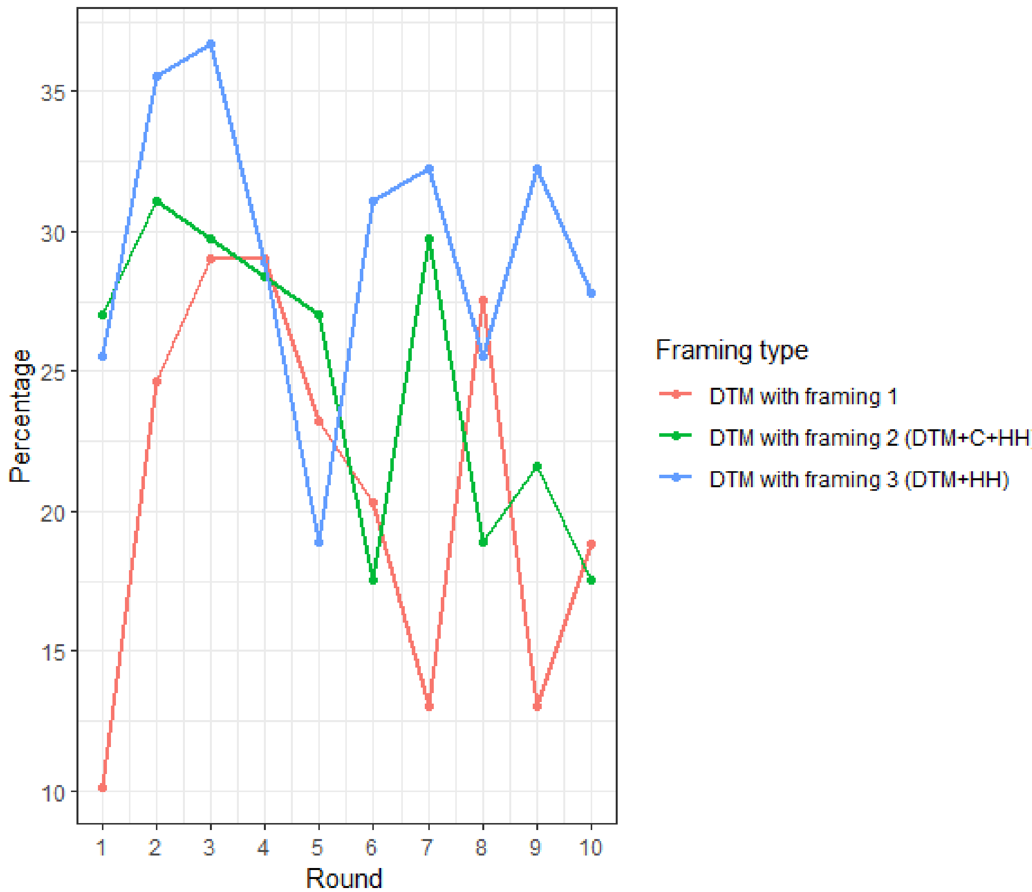


Figure 3.12: Percentage of Farmers Selecting The DTM Bundle by Framing.

3.5 Empirical Approach: How the Game Affects Behaviors

During the experimental game developed for this thesis, the set of options from which the farmer has to decide what bundle to choose represents a discrete and unordered set. Additionally, I assume that the choice of the bundle is a function of the features of the alternative as well as a function of the features of the farmer making the choice, which may add heterogeneity at the aggregate level in the option selected. Furthermore, the data collected during the game can be considered a mix between stated preferences and revealed preferences of a choice, since we are actually observing what the individual chooses, albeit in a simulated environment. Notice that although the farmer playing the game has a clear knowledge of their preferences (U_i), I ignore what exactly those preferences are. However, I can approach those unobservable latent preferences through observable characteristics of the alternatives and the farmer. This white noise or randomness from my perspective leads me to assume a Random Utility Maximization (RUM) model in formulating my empirical approach, where the utility of the individual i under the alternative k is given by $U_{ik} = V_{ik}(\hat{\beta}_i, \hat{\gamma_{ik}}, X_{ik}, Z_i) + \epsilon_i$, with the representative term $V_{ik}(\cdot)$ meaning the utility observable to the researcher through the alternative features X_{ik}, the farmer features Z_i and their estimated parameter $\hat{\beta}_i$ and $\hat{\gamma_{ik}}$, respectively. ϵ_i represents the unobservable portion of the utility which follows an identical independent distribution (iid) extreme value type I. A RUM model will be used to answer the hypothesis formulated for this thesis: Whether a virtual game can change farmers' behaviors through learning mechanisms and whether framing messages significantly affect farmers' choices by influencing their preference weighting, increasing the adoption rate of new technologies.

Since my variable of interest — the input bundle chosen — consists of an unordered discrete set of more than two options, I will implement a polytomous choice model as my empirical approach. Here the farmer will choose the option that gives them the highest utility. In order to estimate the deterministic component of the utility, I will use a mix of the following set of variables:

$$Prob(Y_{it} = L_k) = f(Rnd_t, F_n, \mathbf{B_i}, \mathbf{Exp_{it}}, \mathbf{Soc_i}) \tag{3.1}$$

Where Y is equal to the prospect chosen in a given round of the game. $\mathbf{Rnd_t}$ indicates whether the farmer is playing the first half of the game —rounds 1 to 5 — or the second haft of the game — rounds 6 to 10. This distinction is made considering that by the fifth round, all farmers playing the game should have experienced a drought event during the game so that everyone could consider these experiences gained during the first half of the game when making decisions during the second half of the game. $\mathbf{F_n}$ represents any of the three possible framing messages to which the farmer will be exposed, with $n \in [1, 3]$. $\mathbf{B_i}$ represents farmers' belief about the probability of the occurrence of future weather events and the performance of the inputs under each of these scenarios. $\mathbf{Exp_{it}}$ represents the experiences that farmers have had with the inputs and weather. $\mathbf{Soc_i}$ represents different sociodemographic features of the farmers. The sub-indexes i and t allow for variation by the individual and time, respectively. All these components may condition the farmers' probability of choosing a particular prospect L_k.

Notice that all the components I consider in Equation 3.1 correspond to the individual's characteristics. Therefore, I am going to evaluate how the $K \times 1$ vector of observable variables $\mathbf{Z_i} = \{\mathbf{Rnd_t}, \mathbf{F_n}, \mathbf{B_i}, \mathbf{Exp_{it}}, \mathbf{Soc_i}\}$ affects the decision of choosing an alternative L_k. Particularly, I will evaluate if the probability of choosing the technology increases once the farmer has learned about the performance of the inputs under different weather events by the second half of the game Rnd_t and for the farmers exposed to the family and community framing F_n controlling by the individual features $\mathbf{B_i}, \mathbf{Exp_{it}}, \mathbf{Soc_i}$. For this purpose, I will use a Multinomial Logit (MNL) model to estimate the vector of parameters $\alpha_{\mathbf{j}}$ associated with this vector $\mathbf{Z_i}$. The representative utility is assumed to be linear in the parameters such that the utility for any given alternative k for the individual i takes the following form:

$$\begin{aligned} U_{ik} =& \mathbf{Z_i'} \cdot \alpha_\mathbf{k} + \epsilon_\mathbf{ik} \\ =& V_{ik} + \epsilon_\mathbf{ik} \end{aligned} \tag{3.2}$$

The probability of the farmer choosing option L_k will be defined by the log-likelihood estimator as follows:

$$\begin{aligned} Pr(Y_{it} = L_k|Z_i) &= Pr(U_{ik} > U_{ij} \ \ |Z_i) \\ &= Pr(V_{ik} + \epsilon_{ik} > V_{ij} + \epsilon_{ij} \ \ |Z_i)) \\ &= Pr(V_{ik} - V_{ij} > \epsilon_{ij} - \epsilon_{ik} \ \ |Z_i) \ \forall \ \ k \neq j \end{aligned} \tag{3.3}$$

Given that I assume $\epsilon \sim iid$ extreme value type I, the difference between the errors distributes logistic, thus:

$$Pr(Y_{it} = L_k|Z_i) = \frac{exp(V_{ik})}{\sum_{j=1}^{J} exp(V_{ij})} \tag{3.4}$$

However, under the MNL model we have to normalize the parameters of one of the alternatives, let's say $\alpha_1 = \mathbf{0}_{i1}$, such that the parameters of the other alternatives are interpreted relative to this baseline alternative. This will change our probability function in equation 3.4 as follows:

$$P_{ik} = Pr(Y_{it} = L_k|Z_i) = \frac{exp(V_{ik})}{1 + \sum_{j=2}^{J} exp(V_{ij})} = \Lambda(V_{ik}) \tag{3.5}$$

And the marginal effect would be given by:

$$\frac{\partial P_{ik}}{\partial Z_i} = P_{ik} \cdot \left[\alpha_k - \sum_{k}^{K} P_{ij}\alpha_j \right] \tag{3.6}$$

The following two sections will present the specification of the models implemented to test Hypothesis 1 and Hypothesis 2.

3.5.1 Testing Hypothesis I

For the model estimation under Hypothesis 1, I will take two different approaches. Since the main goal here is to test whether the game teaches farmers about the performance of the input bundles under different weather conditions and consequently modifies farmers' behavior, I will start by testing for differences in means between the first round and the last round of the game when choosing one of the input bundles available. For this setup, I assume that in the first round of the game, the farmer is making decisions with their original beliefs, without having yet played the game. Further, I assume that in the last round, farmers make their final decision by incorporating into their decision-making process all the experience and learning gained during the previous rounds of the game. Therefore, although this experiment does not have yet a follow-up to see the long-term impact of the game, I can still compare the immediate impact of the game by the revealed preferences in the first round — without *treatment* — versus the last round of the game, once the experimental treatment is given.

In order to test if the share of respondents selecting a given input bundle before and after the treatment changes, I will perform a t-test using Stata software. Specifically, I will perform a paired t-test since I will evaluate if there is any significant difference in the input bundle chosen within the same group of farmers who played the game between two moments in time, round 1 and round 10. Here I account for the fact that the sample is the same in both moments of time, thus, not independent of one another. This method will give us a preliminary insight into whether the game has an impact on farmers' behaviors.

Secondly, since the experimental game was designed such that all farmers will have experienced a drought event by the fifth round of the game, I assume that during the second half of the game —between rounds 6 and 10 — the farmer will incorporate their experience learned during the first half of the game. This also allows us to consider all the information collected during the game. Thus, for the second approach I will evaluate the impact that playing the second half of the game has on the probability of adopting one of the input bundles. For this purpose, I will estimate a MNL model where the outcome variable $Y_{it} = \{Matuba(A), DTM(B), DTM + II(G)\}$ represents the set of prospects, with Matuba set as the baseline alternative. The probability of choosing $Y_{it} = L_k$ (bundles B or G relative to bundle A) given that the farmer is playing the second half of the game will be initially evaluated under the following econometric model:

$$Pr(Y_{it} = L_k) = \Lambda(\widehat{\delta_0} \cdot Rnd_t) \tag{3.7}$$

Where Λ is the standard logistic function as described in equation 3.5 and Rnd_t represents here whether the farmer is making decisions in the first 5 rounds of the game or the last 5 rounds of the game.

Finally, to test whether the experience with drought events during the game may be driving the effect of the change in behaviors during the second half of the game, I will add to the model 3.7 control variables that capture whether the farmer was exposed to a mild drought event during the previous round ($LMD_{i,t-1}$), whether the farmer was exposed to a covariate severe drought in the previous round ($LCD_{i,t-1}$), and whether they have yet experienced any of those events up to the current round being played ($ExpLMD_{it}$ and $ExpLCD_{it}$, respectively). Thus, the model 3.7 will be expanded as follows:

$$Pr(Y_{it} = L_k|Z_i) = \Lambda(\widehat{\delta_{0_2}} \cdot Rnd_t + \widehat{\delta_1} \cdot LMD_{i,t-1} + \widehat{\delta_2} \cdot LCD_{i,t-1} + \widehat{\delta_3} \cdot ExpLMD_{it} + \widehat{\delta_4} \cdot ExpLCD_{it}) \tag{3.8}$$

Where the subscript i represents the individual respondent and t represents the round being played, with $t \in [1, 10]$.

3.5.2 Testing Hypothesis II

For the model estimation under Hypothesis 2, first I will consider the impact of the framing on the probability of choosing each technology. I will continue to use MNL, starting with a simple model including only dummy variables for the framing received by a household (F_n with $n \in [1, 3]$ representing one of the 3 framing messages) and a vector of household characteristics.

$$Pr(Y_{it} = L_k|Z_i) = \Lambda(\widehat{\beta_0} \cdot F_n + \mathbf{X_i'}\widehat{\alpha_1}) \tag{3.9}$$

The vector $\mathbf{X_i'}$ in Equation 3.9 represents the vector of variables added to the model to control for social heterogeneities. The control variables include: respondent characteristics (age, sex, education level, whether the respondent makes the decision in the household, and an estimated of their risk aversion level following Cai et al. (2015)); household characteristics (the level of wealth of the household measured by a poverty score built using the most updated Poverty Probability Index (PPI) guidance for Mozambique, awareness of improved seed varieties and index insurance, percentage of household income that came from selling crops, household size, number of children, income sources, access to improved seed, and insurance experience); the household agricultural practices and plot features (average harvest per plot, number of plots, and use of improved or local seed); respondents belief and perceptions (relative harvest using improved seed versus local seed under different weather conditions and their perceived probability of experiencing different weather events); and climate-related risk experiences (whether they have experienced mild drought or severe drought that damage their crops). These variables differ by individual i but are constant across all rounds of the game, so no t subscript is included.

Under this estimation, I will evaluate whether there is a direct impact of the framing on farmers' input decisions by estimating the average marginal effect of being exposed to the family and community framing messages (Framing 2 and Framing 3) relative to being exposed just to the individual framing (Framing 1), which represents the base level for comparison. I will calculate the average marginal effects using the software Stata (see Equation B.1 in Appendix B for a mathematical representation of the marginal effects for Equation 3.9).

There could be differences in the impact of the framing on farmers' behavior as a function of farmers' heterogeneous experiences with drought events. Further, farmers who have been recently exposed to real-world drought events may react differently to a drought experience while playing the game. For those reasons, I extend the model as described in equation 3.10, including as control variables the experience with drought during the game and in real life and the interaction between both of them, isolating the effect of the framing on the decision-making during the game while keeping the other factors constant:

$$Pr(Y_{it} = L_k|Z_i) = \Lambda(\widehat{\beta_1} \cdot F_n + \widehat{\beta_2} \cdot RD_i + \widehat{\beta_3} \cdot LD_{i,t-1} + \widehat{\beta_4} RD_i \cdot LD_{i,t-1} + \mathbf{X_i'}\widehat{\boldsymbol{\alpha_2}}) \quad (3.10)$$

Here the dummy variable RD_i indicates whether the farmer has experienced drought events in real life in the past two agricultural seasons proceeding the household survey. The dummy variable $LD_{i,t-1}$ indicates whether the farmer experienced a drought during the simulation in the crop season adjacent to the current season being played. Incorporating these variables acknowledges the role of actual and simulated drought on farmers' decisions. Furthermore, the interaction term between RD_i and $LD_{i,t-1}$ determines whether the effect on the decision of a drought event during the game would be different if the farmer has experienced drought in real life (see equation B.2 in Appendix B for a mathematical representation of the average marginal effect of the simulated drought on farmers' choice).

Finally, I also want to explore whether the impact of the framing may be different across groups. Particularly, whether it increases with the "right" population of farmers who have been vulnerable to droughts either in real life or during the simulation. One would think that the effect that the game and the framing can have would be stronger for farmers who had experienced drought in the past and also during the game since the new technologies are meant to help the farmers who have been vulnerable to drought events. Thus, farmers that are already vulnerable to droughts may be the most sensitive to the framing and may be more likely to choose the new technologies since they recognized they may need them to mitigate the risk of another drought season. For this reason, I added in equation 3.11 the interaction term of the framing with the droughts experienced (for a mathematical expression for the average marginal effect for equation 3.11 see equation B.3 in Appendix B):

$$\begin{aligned} Pr(Yit = L_k|Z_i) =&\Lambda(\widehat{\beta_5} \cdot F_n + \widehat{\beta_6} \cdot RD_i + \widehat{\beta_7} \cdot LD_{i,t-1} + \widehat{\beta_8} RD_i \cdot LD_{i,t-1} + \\ &\widehat{\beta_9} F_n[\widehat{\gamma_1} LD_{i,t-1} + \widehat{\gamma_2} RD_i + \widehat{\gamma_3} RD_i \cdot LD_{i,t-1}] + \mathbf{X_i'}\widehat{\alpha_3}) \end{aligned} \tag{3.11}$$

In conclusion, these econometric models will allow me to evaluate how framing affects the probability of choosing a specific bundle and how the real and simulated experiences of the farmer with drought events can intensify the effect of the framing and subsequently affect farmers' choices.

3.6 Results

3.6.1 Results for Hypothesis 1

In this section, I will present the results for Hypothesis 1 obtained following the procedure in Section 3.5.1. The results are presented as follows: First, I will present the results of the paired t-test, as the initial approach to test the impact of the game on farmers' behaviors in the short term —within the game. Later, I will introduce the results of the second approach, where I implement a MNL model to test the impact of the second half of the game after all farmers have experienced a simulated drought event. Within this second approach, I will develop two versions of the MNL model, one that evaluates the direct impact of the group of rounds being played on farmers' input decision —Model 1— and another MNL model that evaluates the impact of the group of rounds being played on farmers' input decision while controlling for the weather events experienced during the game —Model 2.

Table 3.9 shows the results for the paired t-test, where I evaluated if there is any statistically significant difference between the choices farmers make in the first round and the last round of the game. Here the outcome variable is represented by the value of farmer investment, which summarizes the bundles chosen by farmers. The result shows that there is a statistically significant difference ($p < 0.01$) between the value of farmer investment during the first round of the game and the last round. Here it is important to notice that in Round 1 of the game, farmers have not gained yet any experience about the outcomes they could obtain under each combination of input bundles and weather events and the probabilities associated with these events. On the contrary, in Round 10 of the game, farmers have gained all the experience the game can possibly provide. This result provides a first insight into the significant learning effects that a virtual maize farming game can have on farmers' decision-making process and behavior in the short term. Nevertheless, it is important to consider that this is a behavioral change that happens within the game, thus, I can not yet generalize if these changes in the game lead to changes in the real world.

Table 3.9: Paired t-test — Difference in Input Choice Within Mozambiquian Farmer between Rounds 1 and 10 of The Game.

Round	**Obs**	**Mean**	**Std. Err.**
Round 1	235	3,834.04	45.21
Round 10	235	4,075.53	28.63
Diff.	235	-241.48***	44.92

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
H_0 : mean(diff)= 0

Now, in order to determine how the decision change during the game, I considered the change in the input bundle chosen during the first half of the game versus the second half of the game, accounting for the fact that by round number 6, every farmer should have experienced at least a drought event. Table 3.10 shows the results for this second approach. Here, Model 1 and Model 2 show the average marginal effects for each of the variables of interest from Equations 3.7 and 3.8, respectively.

The results in Model 1 show that during the second half of the game, farmers tend to reduce their adoption of the traditional Matuba bundle, compared to the first half of the game, with an associated probability of 3.66 percentage points. Additionally, farmers are also more likely to reduce the adoption of the DTM bundle by 3.32 percentage points relative to the first half of the game. Contrary, it seems that after learning from the experience gained during the first half of the game, farmers are 6.98 percentage points more likely to choose the DTM+II bundle during the second half of the game relative to the first half. This result shows that playing some rounds of the simulated game (5 rounds for this case) is enough to produce a learning effect on farmers and change their decision on what input bundle to implement in their following agricultural campaign (see Figure B.1 in Appendix B for a visual representation of the change in the adoption of each bundle during the last 5 rounds of the game relative to the first 5 rounds).

Nevertheless, when adding the experience with droughts during the game as control variables to the model as a robustness check, the change in behaviors that was explained just to be in the second half of the game loses power (see Model 2 in Table 3.10). This indicates that a big portion of this variation is being absorbed by the fact that farmers have already experienced droughts before making a decision on what inputs to use in their next season. The result in Model 2 shows that having any experience with mild drought seasons in the past rounds of the game reduces by 4.09 percentage points the likelihood that farmers choose the traditional Matuba bundle compared to those who have not experienced yet a mild drought during the game (see graph B.2 in Appendix B for a visual representation). Furthermore, having suffered a covariate drought season in the immediately previous agricultural campaign will increase by 7.3 percentage points the probability that farmers choose the DTM+II bundle compared to those who have not experienced a lagged covariate drought event (see graph B.3 in Appendix B for a visual representation). Additionally, the effect of having ever experienced a covariate drought shows a similar pattern for the adoption of the DTM+II bundle, but its effect is smaller in magnitude (5.33 percentage points) and not statistically significant. These results show the importance of remembering farmers constantly -at least in the short term- about the potential benefits that index insurance can bring in order to increase its adoption rate. Farmers seem more willing to acquire the insurance bundle as soon as they have previously experienced a covariate severe drought which reveals the benefits of having it in order to mitigate the impact that a severe drought can have on their crops and livelihood.

Table 3.10: Average Marginal Effects of The Multinomial Logit Models for Hypothesis 1.

	Model 1			Model 2		
	Outcome: Input bundle chosen			*Outcome: Input bundle chosen*		
	Matuba	DTM	DTM+II	Matuba	DTM	DTM+II
Last 5 Rounds	-0.0366^{***}	-0.0332^{*}	0.0698^{***}	0.0067	-0.0289	0.0223
(Rnd_t)	(-2.84)	(-1.86)	(3.53)	(0.26)	(-0.91)	(0.62)
Lagged Mild Drought				0.0213	-0.0261	0.0048
($LMD_{i,t-1}$)				(1.20)	(-1.19)	(0.19)
Lagged Cov. Drought				-0.0321	-0.0408	0.0730^{**}
($LCD_{i,t-1}$)				(-1.53)	(-1.41)	(2.24)
Had Mild Drought				-0.0409^{*}	0.0203	0.0206
($ExpLMD_{it}$)				(-1.90)	(0.80)	(0.70)
Had Cov. Drought				-0.0372	-0.0161	0.0533
($ExpLCD_{it}$)				(-1.32)	(-0.46)	(1.35)
McFadden's R2		0.003			0.009	
AIC		1.752			1.762	
N		2350			2350	

Note: t statistic in parentheses. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$

All variables in the table correspond to the game experience. The variable *Last 5 Rounds* is equal to 1 if the farmer is playing any of the last 5 rounds of the game —round 6 to 10—, 0 otherwise. The variable *Lagged Mild Drought* is equal to 1 if the farmer experienced mild drought in the previous round to the one being played, 0 otherwise. The variable *Lagged Cov. Drought* is equal to 1 if the farmer experienced covariate drought in the previous round to the one being played, 0 otherwise. The variables *Had Mild Drought* and *Had Cov. Drought* are equal to 1 if the farmer has ever experienced a mild or covariate drought, respectively, in any of the previous rounds played, and 0 otherwise. In parenthesis is the name for the variables given in the Empirical approach Section 3.5.

3.6.2 Results for Hypothesis 2

In this section, I will present the results for Hypothesis 2 obtained following the procedure described in Section 3.5.2. I will once again estimate the three models via MNL regression and calculate the average marginal effects of being exposed to each Framing on the bundle chosen. For the first model, I will predict the probability of choosing an input bundle by different Framing messages after controlling for social heterogeneities. For the second model, I will include additional control variables related to the simulated drought experiences farmers have during the game, interacting the real-world drought experiences with the simulated droughts. For the final model, I will estimate the margins at representative values, allowing the effect of the Framing to differ for different groups based on farmers' real and simulated drought experiences, interacting the Framing with the real and simulated droughts. This third model will be split into three versions that calculate the marginal effects of the framing for farmers that have different experiences with: Mild drought events; severe drought events; and a mix of both, mild and severe drought events.

The initial set of general control variables ($\mathbf{X}$) selected for this section includes all variables collected related to farmers' beliefs about the probability of occurrence of weather events and the performance of inputs under each of these different conditions; variables related to farmers' real-world experience with the different input bundles and weather events; and sociodemographic features of the household. All these variables were considered as part of the *super* model version, meaning the model with all the initial variables considered as controls. Then, I developed a *nested* version of the model removing some of the variables that were considered to be not very relevant or that their effect could be captured by other control variables in the model and that also showed to be statistically not significant in the *super* model version. Later, I evaluated the joint significance of the variables excluded as predictors of the model (together) using the likelihood ratio test. The result showed that the variables excluded in the nested model do not statistically significantly improve the model fit (See Table B.2 in Annexes B). Additionally, when comparing the AIC and

McFadden R^2 criteria for logistic model selection, the nested model has the lowest and highest value, respectively, indicating also that this model has a better fit, the reason why I decided to stay with the nested version of the model.

Table 3.11: Average Marginal Effects of The Multinomial Logit Model 1 for Hypothesis 2.

	Model 1		
	Outcome: Input bundle chosen		
	Matuba	DTM	DTM+II
Framing			
Community & HH	-0.0584^{***}	-0.0463	0.105^{***}
(Framing 2)	(-2.62)	(-1.57)	(3.27)
HH Only	-0.0146	0.0320	-0.0174
(Framing 3)	(-0.64)	(1.10)	(-0.56)
McFadden's R2		0.122	
AIC		1.737	
N		1,480	

Note: t statistic in parentheses. $^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$

Besides the variables of interest shown in the table, this model also includes the set of control variables **X**, where farmers' experience with real-world drought events is considered. The variables *Community & HH framing* (Framing 2) and *HH Only framing* (Framing 3) are part of the three categories' variable *Framing* and are expressed in relative terms to the individual framing, which here represents the baseline level for the *Framing* variable. Framing 2 induces farmers to think not just about the individual benefit that the DTM+II bundle brings in terms of yield, but also about how this bundle can mitigate the impact of droughts on their household livelihood and community well-being. Framing 3 also considers the individual benefit of the DTM+II bundle in terms of yield and the benefits for the household's livelihood.

Table 3.11 shows the results for the first model described in Equation 3.9 to test Hypothesis 2. Here, Model 1 shows the average marginal effects of Framing 2 and Framing 3 relative to Framing 1 on farmers' decision-making within the game. The results show that the framing that drives farmers to think about their family and community livelihood and well-being — framing 2 — significantly increases the adoption of the DTM seed and index insurance bundle by 10.5 percentage points compared to the baseline framing that only mentions the individual benefits of this bundle in term of maize yield. New adopters of the DTM+II bundle come from farmers previously using both, Matuba and DTM without insurance. The biggest reduction is in the Matuba use, where farmers exposed to Framing 2 are 5.8 percentage points less likely to adopt the Matuba bundle compared to those under the baseline treatment, Framing 1. This gave us some insights for the evaluation of Hypothesis 2 where making farmers consider the benefits of the bundle on the others they care about may increase the utility perceived for this bundle, activating the family and community component of the valuation of a bundle as described in Equation 2.21.

When extending the model to consider farmers' experience with simulated droughts within the game, as described in Equation 3.10, the results do not change meaningfully. Table 3.12 contains the results. Here it is observed the effect of the framing while the rest of the covariates are set to their mean, including the interaction terms between the real world and within-game drought experience. Similar to what was found in Table 3.11, farmers' exposure to the framing that recalls the value of the DTM seed and index insurance bundle on the family and community well-being increases the probability of choosing that bundle by 10.7 percentage points relative to being exposed to the individual framing. Here, new adopters come also from both, farmers previously using Matuba and DTM without insurance, with the biggest reduction in the Matuba use. Being exposed to Framing 2 reduces the likelihood of choosing the Matuba bundle by 5.9 percentage points relative to being exposed to the individual framing.

Table 3.12: Average Marginal Effects of The Multinomial Logit Model 2 for Hypothesis 2.

	Model 2		
	Outcome: Input bundle chosen		
	Matuba	DTM	DTM+II
Framing			
Community & HH	-0.0595^{***}	-0.0476	0.107^{***}
($Framing\_2$)	(-2.60)	(-1.55)	(3.28)
HH Only	-0.0224	0.0062	0.0163
($Framing\_3$)	(-1.02)	(0.22)	(0.54)
McFadden's R2		0.121	
AIC		1.771	
N		1,480	

Note: t statistic in parentheses. $^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$

Besides the variables of interest shown in the table, this model also includes the set of control variables **X**, where farmers' experience with real-world drought events is considered. In addition to Model 1, here I also include control variables of lagged droughts experiences within the game and the interaction between the lagged droughts experiences within the game and the real-world droughts experiences, for both, mild and severe droughts. The variables *Community & HH framing* (Framing 2) and *HH Only framing* (Framing 3) are part of the three categories' variable *Framing* and are expressed in relative terms to the individual framing, which here represents the baseline level for the *Framing* variable.

Finally, extending the model to the setup in Equation 3.11, where the average marginal effect of the framing considers the "right population" in terms of those who have been vulnerable to the effects of droughts, the results show to be consistent with the previous specifications. For the first model under this setup the interaction term of the Framing with the droughts events experienced during the game and real world are set to their mean as well as the other covariables. Table 3.13 shows the results for this first approach —Model 3.1. Here, the impact of Framing 2 on the probability of choosing the DTM and index insurance bundle is statistically significant and increases by 11.7 percentage points relative to being treated just with the individual framing, keeping all other factors constant at their mean values.

Table 3.13: Average Marginal Effects of The Multinomial Logit Model 3 for Hypothesis 2 — All Covariates Set to their Mean.

	Model 3.1		
	Outcome: Input bundle chosen		
	Matuba	DTM	DTM+II
Framing			
Community & HH	-0.0531^{**}	-0.0636^{**}	0.117^{***}
(Framing 2)	(-2.47)	(-2.15)	(3.77)
HH Only	-0.0153	0.0097	0.0056
(Framing 3)	(-0.74)	(0.34)	(0.19)
McFadden's R2		0.143	
AIC		1.928	
N		1,480	

Note: t statistic in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Besides the variables of interest shown in the table, this model also includes the set of control variables **X**, where farmers' experience with real-world drought events is considered. Here I also include control variables of lagged droughts experiences within the game and the interaction between the lagged droughts experiences within the game and the real-world droughts experiences, for both, mild and severe droughts. In addition to Models 1 and 2, Model 3 also includes the interaction term between the Framing and both, the real-world and simulated lagged drought experiences. The variables *Community & HH framing* (Framing 2) and *HH Only framing* (Framing 3) are part of the three categories' variable *Framing* and are expressed in relative terms to the individual framing, which here represents the baseline level for the *Framing* variable.

Now, for this final model expressed in Equation 3.11, I will allow the effect of the Framing messages to differ based on farmers' real and simulated drought experiences. In order to reflect this, Tables 3.14, 3.15 and 3.16 calculate the marginal effects of the framing for farmers with different drought experiences. Drought experiences will differ by whether the farmer has experienced mild droughts, severe droughts, or a mix of both, respectively.

The results show that the marginal effects, at representative values, of the framing on the probability of choosing a certain bundle under Model 3.11 differs greatly by the experiences farmers have had with real and simulated droughts.

Table 3.14 shows the impact of the framing on farmers' decisions when I set to different values the combination of experience with mild drought events in real life and lagged experience with a mild drought event during the game (for a graphical representation of these results see Figure B.4 in Appendix B). The results show that having experience with real mild drought events during the 2020-2021 and 2021-2022 agricultural campaigns makes farmers more sensitive to the treatment of the framing compared to those who have not had real experiences with mild drought events. Furthermore, the impact of Framing 2 increases for those who had experienced real mild drought compared to the results obtained in Table 3.13. For those who had experienced real mild droughts and also lagged mild drought during the game, being exposed to Framing 2, which makes farmers think about their family in the community previously to making a decision, increases the probability of farmers choosing the drought-tolerant improved seed and index insurance bundle by 35.41 percentage points compared to those who were exposed to Framing 1. New adopters of the DTM+II bundle come from farmers previously using both, Matuba and DTM without insurance inputs, where being exposed to Framing 2 reduces the probability of choosing the Matuba or DTM bundle reduces by 18.27 and 17.14 percentage points respectively, compared to those exposed to the individual framing.

In contrast, for the farmers who were exposed to Framing 2 and had experienced just real mild drought in their previous two seasons but not lagged mild drought during the game, the probability of choosing the drought-tolerant improved seed and index insurance bundle increased by 26.9 percent points compared to those exposed to Framing 1. New adopters of the DTM+II bundle also come from both, previous adopters of the Matuba and DTM without insurance bundle. Here, the probabilities to adopt the Matuba and DTM bundles drop by 5 percentage points and 11.9 percentage points, respectively, compared to those exposed to Framing 1.

The results for farmers exposed to Framing 3 are less consistent. For farmers exposed to Framing 3 and that have experienced real mild drought but not lagged mild drought, the probability of choosing the DTM+II also increases compared to those exposed to Framing 1, this time by 12.9 percentage points. In this case, the increase in the adoption of DTM+II comes from farmers who previously use Matuba as their crop input, where the probability of choosing the Matuba bundle reduces for these farmers by 13.4 percentage points compared to those exposed to Framing 1. Interestingly, if the farmer has experienced a lagged mild drought during the game but not in real life, the exposure to Framing 3 shows to increase the probability of choosing the Matuba bundle by 8.5 percentage points compared to those exposed to Framing 1. Further, if the farmer has not experienced either real mild drought or lagged mild drought during the game, then being exposed to Framing 3 increases the probability of choosing the DTM bundle by 9.5 percentage points. This increase comes from a reduction in the probability of choosing the DTM+II bundle by 10.5 percentage points, compared to farmers exposed to Framing 1.

These results show the importance of real experience with mild drought for the family and community framing to have a significant effect on farmers' choices. Additionally, the results are consistent with the idea that farmers who only experienced a lagged mild drought may experience financial constraints that lead them to choose the cheapest input bundle for the following crop season. Those who have not experienced either real or lagged simulated mild drought may not have a reason to invest in the most expensive bundle, although the family framing still leads them to choose some kind of protection against drought events — the DTM input.

Table 3.14: Average Marginal Effects of The Multinomial Logit Model 3 for Hypothesis 2 — At Specific Values for Real and Simulated Mild Drought.

	Model 3.2		
	Outcome: Input bundle chosen		
	Matuba	DTM	DTM+II
$\mathbf{RD_i - Mild = 1, LMD_{i,t-1} = 1}$			
Community & HH	-0.1827^{***}	-0.1714^{**}	0.3541^{***}
	(-3.37)	(-2.48)	(5.46)
HH Only	-0.0243	-0.0843	0.1086
	(-0.38)	(-1.21)	(1.62)
$\mathbf{RD_i - Mild = 0, LMD_{i,t-1} = 1}$			
Community & HH	0.0437	-0.0374	-0.0063
	(1.31)	(-0.52)	(-0.08)
HH Only	0.0858^{**}	-0.0132	-0.0726
	(2.47)	(-0.19)	(-1.02)
$\mathbf{RD_i - Mild = 0, LMD_{i,t-1} = 0}$			
Community & HH	-0.0004	0.0748	-0.0744
	(-0.01)	(1.45)	(-1.35)
HH Only	0.0091	0.0957^{*}	-0.105^{**}
	(0.27)	(1.95)	(-2.00)
$\mathbf{RD_i - Mild = 1, LMD_{i,t-1} = 0}$			
Community & HH	-0.150^{***}	-0.119^{**}	0.269^{***}
	(-3.34)	(-2.30)	(5.23)
HH Only	-0.134^{***}	0.0058	0.129^{***}
	(-3.18)	(0.11)	(2.64)
McFadden's R2		0.143	
AIC		1.928	
N		1,480	

Note: t statistic in parentheses. $^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$

Besides the variables of interest shown in the table, this model also includes the set of control variables **X**. Farmers' experience with real and simulated drought events is also considered in the model. In contrast to Model 3.1., this model differentiates the sample by: 1) whether the farmer has experienced a mild drought event in real life, represented by 1 in the variable $RD_i - Mild$, 0 otherwise, and 2) whether the farmer has experienced a lagged mild drought event during the game, represented by 1 in the variable $LMD_{i,t-1}$, 0 otherwise. The variables *Community & HH* (Framing 2) and *HH Only* (Framing 3) are part of the three categories' variable *Framing* and are expressed in relative terms to the individual framing, which here represents the baseline level for the *Framing* variable.

On the other hand, the results in Table 3.15 show the impact of the framing messages setting to different values a combination between farmers' real experience with severe drought events during their 2020-2021 and 2021-2022 agricultural campaign and lagged severe droughts during the simulated game (for a graphical representation of these results see Figure B.5 in Appendix B). Consistently with the previous results, having experienced real severe drought increases the impact of the framing compared to the average results in Table 3.13. Here, farmers who had experienced real severe droughts and also lagged severe drought during the game and that are exposed to the family and community framing -Framing 2- are more likely to choose the DTM+II bundle compared to those exposed to Framing 1, by 31.3 percentage points. This increase in the probability of adopting the DTM+II bundle comes mostly from a decrease in the probability of farmers choosing the DTM bundle, by 26.9 percentage points, compared to farmers exposed to Framing 1. Unlike the results with exposure to mild drought, here being exposed to Framing 3 seems to have a statistically significant impact whenever farmers have experienced severe drought in real life and during the game. Being exposed to Framing 3 increases the probability of choosing the DTM+II bundle by 20 percentage points compared to being exposed to Framing 1. New adopters of the DTM+II bundle come mostly from farmers previously using the DTM bundle, where the probability of choosing DTM without insurance decreases by 17.8 percentage points compared to being exposed to Framing 1.

Framing 2 also shows to have an impact on farmers who had experienced real severe droughts but not a lagged severe drought during the game. For these farmers, the probability of choosing the DTM+II bundle increases by 21.4 percentage points compared to those exposed to Framing 1. Here the increase in adopter for the DTM+II bundle come from farmers previously using both, Matuba and DTM, where the probability of choosing Matuba or DTM bundles reduces by 9 and 12.3 percentage points, respectively, relative to those exposed to Framing 1. Thus, the biggest reduction is in the use of DTM without insurance.

For those who have not experienced neither a real-world severe drought nor a simulated lagged severe drought, the exposure to Framing 2 and Framing 3 increases the probability of choosing the DTM input without insurance by 13.1 and 9.3 percentage points, respectively, relative to being exposed to Framing 1. For both, Framing 2 and Framing 3, the increase in the number of adopter of DTM without insurance come mostly from farmers previously using the DTM+II bundle. This result could be explained by the fact that farmers may not expend a lot of resources on the insurance bundle if they do not perceive its value due to the lack of experience with severe droughts. Nevertheless, the family and community framing still drive farmers to search for protection through the adoption of the DTM input, compared to those exposed to the individual framing.

Table 3.15: Average Marginal Effects of The Multinomial Logit Model 3 for Hypothesis 2 — At Specific Values for Real and Simulated Severe Drought.

	Model 3.3		
	Outcome: Input bundle chosen		
	Matuba	DTM	DTM+II
$\mathbf{RD_i - Severe = 1, LSD_{i,t-1} = 1}$			
Community & HH	-0.0442	-0.269^{***}	0.313^{***}
	(-0.94)	(-3.12)	(3.62)
HH Only	-0.0226	-0.178^{*}	0.200^{**}
	(-0.45)	(-1.94)	(2.17)
$\mathbf{RD_i - Severe = 0, LSD_{i,t-1} = 1}$			
Community & HH	0.0624	-0.0223	-0.0401
	(1.12)	(-0.26)	(-0.42)
HH Only	0.0447	-0.00280	-0.0419
	(0.97)	(-0.03)	(-0.45)
$\mathbf{RD_i - Severe = 0, LSD_{i,t-1} = 0}$			
Community & HH	-0.0448	0.131^{**}	-0.0867
	(-1.44)	(2.27)	(-1.45)
HH Only	0.0152	0.0936^{*}	-0.109^{*}
	(0.40)	(1.68)	(-1.86)
$\mathbf{RD_i - Severe = 1, LSD_{i,t-1} = 0}$			
Community & HH	-0.0904^{***}	-0.123^{***}	0.214^{***}
	(-2.61)	(-2.85)	(4.66)
HH Only	-0.0511	-0.0007	0.0519
	(-1.57)	(-0.02)	(1.18)
McFadden's R2	0.143		
AIC	1.928		
N	1,480		

Note: t statistic in parentheses. $^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$

Besides the variables of interest shown in the table, this model also includes the set of control variables **X**. Farmers' experience with real and simulated drought events is also considered in the model. In contrast to Model 3.1., this model differentiates the sample by: 1) whether the farmer has experienced a severe drought event in real life, represented by 1 in the variable $RD_i - Severe$, 0 otherwise, and 2) whether the farmer has experienced a lagged severe drought event during the game, represented by 1 in the variable $LSD_{i,t-1}$, 0 otherwise. The variables *Community & HH* (Framing 2) and *HH Only framing* (Framing 3) are part of the three categories' variable *Framing* and are expressed in relative terms to the individual framing, which here represents the baseline level for the *Framing* variable.

Finally, table 3.16 shows the results for farmers who had experienced both severe and mild drought during the game and in real life during the 2020-2021 and 2021-2022 agricultural campaigns and also when farmers had experienced none of them. The impact of Framing 2 and Framing 3 relative to Framing 1 shows to be stronger for farmers who had experienced all of these drought events compared to the previous results when I adjusted the predictions only for one type of drought. The impact of Framing 2 on farmers exposed to all of these drought events increases by 51.5 percentage points the probability of choosing the DTM+II bundle, which comes mostly from a reduction in 40.3 percentage points on the probability of choosing the DTM relative to Framing 1. On the other hand, Framing 3 increases the probability of choosing the DTM+II bundle by 31.1 percentage points, coming mostly from a reduction in the probability of choosing the DTM bundle, by 28.8 percentage points relative to Framing 1.

For farmers who had experienced neither severe nor mild drought during the game or in real life in the two previous agricultural campaigns, the impact of the framing on farmers' decisions was negative. In this case, Framing 2 and Framing 3 reduce the probability of choosing the DTM+II bundle by 27.5 and 21.2 percentage points relative to Framing 1. This result makes sense since these types of farmers are not vulnerable to droughts, thus they do not have the incentive to invest in the most expensive bundle to protect their family and community. Nevertheless, they still search for some type of protection, where being exposed to Framing 2 and Framing 3 increases the probability of choosing the DTM bundle by 28.1 and 17.1 percentage points relative to Framing 1.

Table 3.16: Average Marginal Effects of The Multinomial Logit Model 3 for Hypothesis 2 — At Specific Values for Real and Simulated Severe Drought and Mild Drought.

	Model 3.4		
	Outcome: Input bundle chosen		
	Matuba	DTM	DTM+II
$\mathbf{RD_i - Severe = 1, LSD_{i,t-1} = 1, RD_i - Mild = 1, LMD_{i,t-1} = 1}$			
Community & HH	−0.113	−0.403***	0.515***
	(−1.53)	(−3.45)	(4.97
HH Only	−0.0233	−0.288**	0.311***
	(−0.26)	(−2.28)	(2.59)
$\mathbf{RD_i - Severe = 0, LSD_{i,t-1} = 0, RD_i - Mild = 0, LMD_{i,t=1} = 0}$			
Community & HH	−0.0060	0.281***	−0.275***
	(−0.18)	(3.33)	(−3.24)
HH Only	0.0416	0.171**	−0.212***
	(0.99)	(2.40)	(−2.85)
McFadden's R2		0.143	
AIC		1.928	
N		1,480	

Note: t statistic in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Besides the variables of interest shown in the table, this model also includes the set of control variables **X**. Farmers' experience with real and simulated drought events is also considered in the model. In contrast to Model 3.1., this model differentiates the sample by whether the farmer has experienced all possible drought events in the game and in real life. Variables $RD_i - Severe$ and $RD_i - Mild$ are equal to 1 if the farmer has experienced severe droughts or mild droughts in the real world, respectively, and 0 otherwise. Variables $LSD_{i,t-1}$ and $LMD_{i,t-1}$ are equal to 1 if the farmer has experienced lagged severe drought or lagged mild drought in the game, respectively, 0 otherwise. The variables *Community & HH* (Framing 2) and *HH Only framing* (Framing 3) are part of the three categories' variable *Framing* and are expressed in relative terms to the individual framing, which here represents the baseline level for the *Framing* variable.

CHAPTER 4

DISCUSSION AND CONCLUSIONS

The research developed in this thesis aimed to identify the impact of a virtual maize farming game on farmers' behavior in the short term, namely within the game, in choosing input bundles for use in cultivating maize. Specifically, the hypotheses established for this research were: 1) Simulated experiences will affect farmers' choices by influencing their subjective beliefs about possible outcomes and their probabilities. This influence over farmers' beliefs is caused by the experience acquired while playing the simulated game; 2) Framing will affect farmers' choices by influencing preference weighting, here defined in terms of the domains of self-interest, family, and community. Farmers exposed to the family and community framed messages will have higher adoption of resilience-enhancing technologies compared to those who were not exposed to these framed messages. These hypotheses were tested with farmers in Manica province, Mozambique.

The results for Hypothesis 1 show that the simulated experience produced learning that influenced farmers' input choices during the game, leading them to transition from traditional technologies to resilience-enhancing technologies. Importantly, playing the game is relevant in guiding farmers' decisions as soon as the game provides enough experience about the outcomes farmers may obtain with the different input bundles under drought seasons. Farmers' experience with a mild drought event during any of the previous rounds of the game shows to be the most significant experience in driving farmers away from using traditional maize seed. Further, having experienced a lagged covariate droughts during the game led farmers to adopt the Drought Tolerant Maize (DTM) seed and index insurance (II) input bundle. This shows the importance of constantly reminding farmers about the potential benefits that the insurance bundle can bring in order to increase its adoption rate, at least in the short term. Allowing farmers to experience these drought events at least once during the first 5 rounds of the game shows to be enough for farmers to learn about the outcomes under different weather events and the probabilities of those weather events. Based on this experience, farmers start changing their behaviors during the second half of the game.

Investigating Hypothesis 2 also yielded an interesting set of conclusions. Notably, exposing farmers to the framing that highlights the benefits of the DTM and II bundle to the farmers' household and community well-being, in addition to the individual benefit in terms of yield, led to significant increases in the adoption of these new technologies. Furthermore, the effect of being exposed to the family and community framing interacts meaningfully with a farmer's experience with the real world and simulated droughts. The effect of the framing on farmers' likelihood of adopting the DTM seed and II bundle increases significantly when farmers have experienced drought events in the real world, making them more likely to adopt this bundle. Further, the positive impact of this framing on the adoption of the DTM seed and II bundle increases even more when, on top of having real drought experiences, the farmer has also experienced lagged simulated droughts during the game.

Interestingly, when farmers have experienced a lagged mild drought during the game but not in the real world, and farmers are exposed to the household framing, then the adoption of the traditional bundle increases relative to those exposed to the individual framing. This behavior could be explained by the fact that farmers are left with fewer resources to invest in the following season, and thus choose the cheapest input bundle. Also, the weight of the family domain activated with this framing on the farmers' utility valuation may not be big enough if the farmer has not experienced real mild droughts.

On the contrary, when the farmers have not experienced any of the drought events in the real world nor in the simulated experience, both the household framing and the household-and-community framing result in decreases in the adoption of the DTM and II bundle, relative to exposure to the individual framing. In this case, farmers show an increased likelihood of adopting DTM seed by itself, and there is no significant change in the likelihood of choosing the traditional seed variety. Thus, farmers exposed to the household and community framing messages still show an interest in some kind of protection to mitigate the impact of droughts on their household's and community's livelihood. They will not invest in the most expensive bundle, however, if they do not see the importance of doing so due to the lack of experience with any drought event in the real world and in the game, deciding to save the resources since they may perceive the investment in the insurance bundle as a waste.

These results support the theory formulated in this research, where the introduction of a framed message that makes farmers think about their family and community activates these components in farmers' valuation of the prospects, nudging them to choose a new technology over the traditional input. Nevertheless, in order for the framing messages to nudge farmers to invest in the insurance bundle, it is important that farmers have been exposed before to real drought events. Being exposed to real drought events may make the family and community components of the bundle valuation weigh more heavily on the decision-making process.

The development of this virtual farming game calibrated with local data has proven to be relevant as an educational instrument to introduce new technologies in farmers' communities. The research presented here shows that farmers can learn from this virtual experience and reset their expectations, at least in the short term, regarding the outcomes associated with different agricultural strategies under different weather scenarios, as well as the probabilities of those weather scenarios. Even more, introducing framing messages during the game was shown to affect farmers' preference weighting, activating, in this case, the family and community domains in the valuation of prospects. Thus, both strategies, the game and the framing messages, could be implemented as additional strategies to intensify the adoption of new technologies.

So far the results of the game experiment have internal validity for a sample of small maize farmers in Mozambique. Nevertheless, the game was built to be general enough that it can easily be calibrated to other contexts, including different rainfall levels, different crop yields, and different inputs costs and market prices. It would be interesting for future research to test the instrument in different contexts to evaluate whether the results of the game are consistent under different conditions.

Furthermore, the introduction of framing messages and simulated environments in order to influence behavior may also be affected by the level of loss aversion in farmers. For example, farmers may perceive that their investment in the Bundle of DTM+II represents a loss if the occurrence of a severe drought does not affect the community, leading to no payment. Thus, farmers with higher levels of loss aversion may be more prone to reduce their future investment in the II bundle. However, for this research, we do not measure directly the parameter of loss aversion level, but it would be interesting for future research that uses this method to also evaluate the effect of the instruments allowing farmers to differ by their level of loss aversion.

Additionally, it would be interesting to evaluate the role that farmers' social networks may play in farmers' behavior during the game and after the game. On one side, it would be possible to perceive that farmers with close social ties may behave more similarly during the game compared to those with who they have more social distance. Additionally, it could be evaluated whether the framing messages that attempt to influence farmers' behavior towards the community's well-being may have a bigger effect on farmers who have stronger connectivity to their network or stronger social ties. On the other side, it could be possible that playing the game just with the central nodes in the farmers' community would be enough to disseminate the information about the performance of the new technologies among the other farmers in the community, without the need of investing lot of resources in training every farmer, since these key nodes in the network may diffuse their learning with the others after the intervention. This spillover effect may depend on the degree of connection of the network and on the level of trust farmers have in those central nodes in their community as a source of information. Additionally, it would be necessary to control here by other possible sources of information that farmers may access like media, extension agents, or agricultural exhibitions.

Finally, the results obtained during this research account just for the changes in farmers' behaviors in the very short term —within the game. It would be valuable to see how long the effect of these instruments last and if farmers actually change their behaviors in the real world. The research team for this project will collect follow-up data with the sample that was part of the experiment in 2023, 2024, and 2025. It would be interesting to compare the investment decisions in these years among those who were exposed to the game in 2022 versus those who were not exposed to this virtual experience.

To conclude, the implementation of simulated games and framing messages with small farmers' communities can produce changes in farmers' behaviors through learning mechanisms. Importantly, these types of instruments could help in mitigating the impact that climate change is having on these communities' livelihoods and also help increase farmers' resilience to severe drought events, increasing the community's well-being as a whole.

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APPENDICES: APPENDIX A

CONSENT NOTE

Hello, my name is (name), You are invited to participate in a research project being led by Dr. Jonathan Malacarne, a faculty member in the School of Economics at the University of Maine, U.S.A. Dr. Stephen Boucher from the University of California, U.S.A., and Drs, Meizal Popat and Lourenco Manuel of the Universidade Eduardo Mondlane are also part of the research team.

The purpose of the research is to better understand how maize producers make decisions about agricultural inputs and how they manage weather risk. If you decide to participate, you will be asked to take part in a survey. The survey may take approximately one hour and will contain questions related to agriculture, household decision-making, and household consumption. Your name will not be on any of the data.

Participation is voluntary. You are free to skip any questions you do not wish to answer and you can choose to end the interview at any time. The intent is for you to participate in the survey for four consecutive years, but you may choose to stop at any time.

If you have any questions about this study, please contact Dr. Jonathan Malacarne at (+1) 207 581 3198 or email him at jonathan.malacarne@maine.edu. You may also contact Dr. Malacarne, Dr. Popat, or Dr. Manuel.

APPENDICES: APPENDIX B

SUPPLEMENTARY MODELS

B.1 Balance table for randomization of the game sample by framing

Table B.1: Summary Statistics and Evaluation of Difference in Means —t-test— by Framing.

Variable	(1) Framing 1	(2) Framing 2	(3) Framing 3	Mean Diff. (1) vs (2)	Mean Diff. (1) vs (3)
Plots (#)	1.545	1.662	1.434	-0.117	0.111
	(0.081)	(0.111)	(0.060)		
Total Area (ha)	3.986	4.169	4.836	-0.183	-0.849
	(0.408)	(0.355)	(1.318)		
Area in Maize (ha)	3.025	2.852	2.664	0.173	0.3607
	(0.335)	(0.245)	(0.332)		
Use Any Improved Maize (%)	0.268	0.36	0.268	-0.091	-0.000
	(0.054)	(0.055)	(0.046)		
Use Any DTM (%)	0.045	0.026	0.053	0.019	-0.008
	(0.106)	(0.08)	(0.087)		
Aware of DTM (%)	0.227	0.229	0.25	-0.002	-0.023
	(0.051)	(0.049)	(0.045)		
Aware of Ag. Insurance (%)	0.03	0.0135	0.021	0.016	0.008
	(0.021)	(0.013)	(0.0152)		
Risk aversion (0-1)	0.571	0.547	0.541	0.024	0.031
	(0.054)	(0.052)	(0.047)		
Respondent's age (Avg)	46.818	45.918	46.532	0.899	0.285
	(1.905)	(1.761)	(1.499)		
Male respondents (%)	0.681	0.657	0.641	0.024	0.040
	(0.057)	(0.055)	(0.05)		
Experienced mild drought (%)	0.582	0.40	0.419	0.182**	0.163**
	(0.061)	(0.056)	(0.051)		
Experienced severe drought (%)	0.701	0.693	0.752	0.008	-0.051
	(0.056)	(0.053)	(0.044)		
Observations	67	75	93		

Note: Standard deviation in parenthesis. Mean Diff. represents the value for the difference in means for each variable. Framing 1 represents the baseline framing for comparison. The difference in means in the variables between the groups of farmers exposed to Framing 2 and 3 against those exposed to Framing 1 was evaluated using the t-test with Ho: diff = 0. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$. The experience with real mild and severe droughts is for the period 2020-2022. Based on the t-test results, the randomization of the sample in the 3 framing arms was well-balanced.

B.2 Empirical Multinomial Logit Marginal effects

- The average marginal effect for equation 3.9 is given by:

$$\sum_{i}^{N}\left[\frac{\partial Pr(Y_i = L_k|Z_i)}{\partial F_n}\right]/N = \sum_{i}^{N}\left[\Lambda(V_{ik})\cdot\left[\widehat{\beta_{0k}} - \Lambda(V_{ij_1})\widehat{\beta_{0j_1}} - \Lambda(V_{ij_2})\widehat{\beta_{0j_2}}\right]\right]/N \tag{B.1}$$

Equation B.1 estimates the impact of the framing n relative to the base level framing on the probability of choosing alternative L_k relative to the baseline alternative. The subscripts k, j_1 and j_2 represents the three alternatives, where L_k is the chosen alternative and L_{j_1} and L_{j_2} are the non chosen ones.

- The average marginal effect for equation 3.10 of the simulated drought on farmers' choice during the game is given by:

$$\sum_{i}^{N}\left[\frac{\partial Pr(Y_i = L_k|Z_i)}{\partial LD_{i,t-1}}\right]/N = \tag{B.2}$$
$$\sum_{i}^{N}\left(\Lambda(V_{ik})\cdot\left[(\widehat{\beta_{3k}} + \widehat{\beta_{4k}}RD_i) - \Lambda(V_{ij_1})(\widehat{\beta_{3j_1}} + \widehat{\beta_{4j_1}}RD_i) - \Lambda(V_{ij_2})(\widehat{\beta_{3j_2}} + \widehat{\beta_{4j_2}}RD_i)\right]\right)/N$$

In equation B.2, if the farmer i has been exposed to droughts in real life then $RD_i = 1$. If the farmer has not been exposed to real droughts, then $RD_i = 0$.

- The average marginal effect for equation 3.11 of the framing on farmers' choice will be given by:

$$\sum_{i}^{N}\left[\frac{\partial Pr(Y_i = L_k|Z_i)}{\partial F_n}\right]/N = \tag{B.3}$$
$$\sum_{i}^{N}(\Lambda(V_{ik})\cdot[(\widehat{\beta_{5k}} + \widehat{\beta_{9k}}[\widehat{\gamma_{1k}}LD_{i,t-1} + \widehat{\gamma_{2k}}RD_i + \widehat{\gamma_{3k}}RD_i \cdot LD_{i,t-1}])$$
$$- \Lambda(V_{ij_1})(\widehat{\beta_{5j_1}} + \widehat{\beta_{9j_1}}[\widehat{\gamma_{1j_1}}LD_{i,t-1} + \widehat{\gamma_{2j_1}}RD_i + \widehat{\gamma_{3j_1}}RD_i \cdot LD_{i,t-1}])$$
$$- \Lambda(V_{ij_2})(\widehat{\beta_{5j_2}} + \widehat{\beta_{9j_2}}[\widehat{\gamma_{1j_2}}LD_{i,t-1} + \widehat{\gamma_{2j_2}}RD_i + \widehat{\gamma_{3j_2}}RD_i \cdot LD_{i,t-1}])])/N$$

In equation B.3, $RD_i = 0$ if the farmer i has not experienced yet drought in real life, otherwise $RD_i = 1$. Also, if the farmer has not experienced simulated drought in the previous season during the game, then $LD_{i,t-1} = 0$, otherwise $LD_{i,t-1} = 1$.

- Average marginal effect for MNL model 1 in Table 3.10, representing the probability of change in the selection of each bundle during the last half rounds of the game relative to the first half:

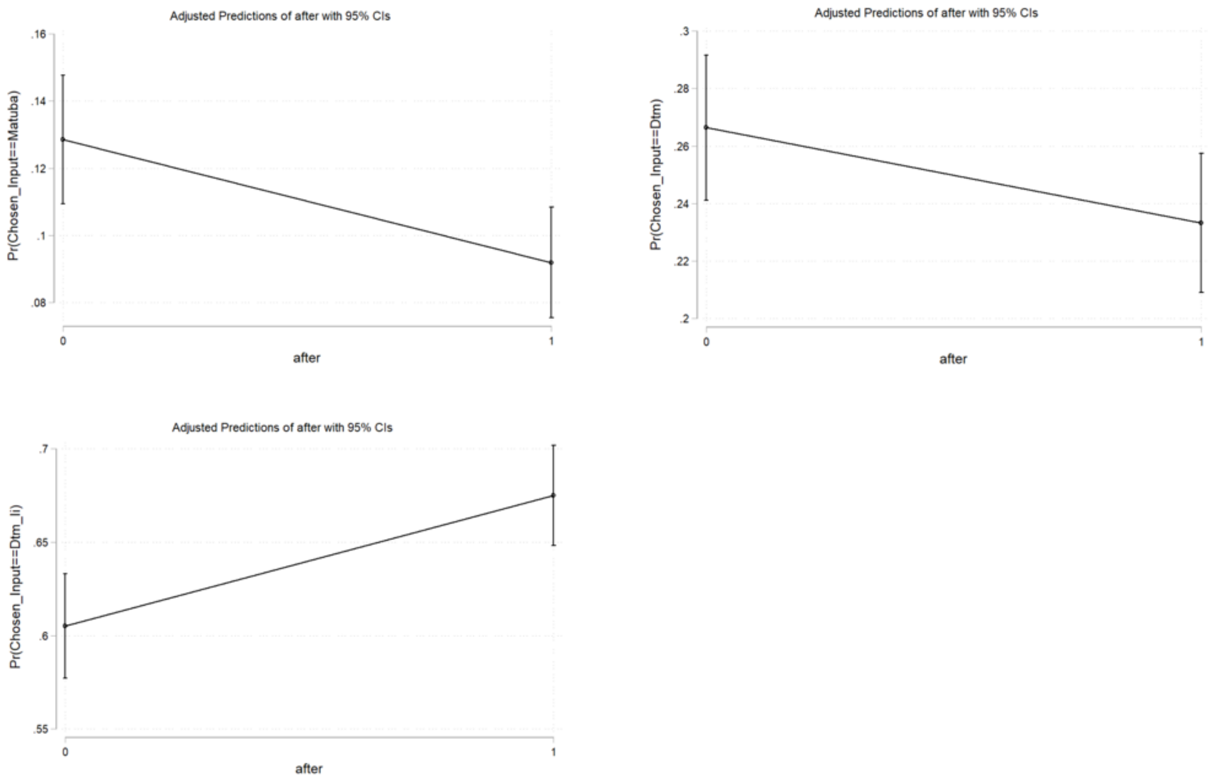

Figure B.1: Average Marginal Effects — Model 1.

- Average marginal effect for MNL model 2 in Table 3.10, for the covariable of whether the farmer had ever experienced a mild drought during the game:

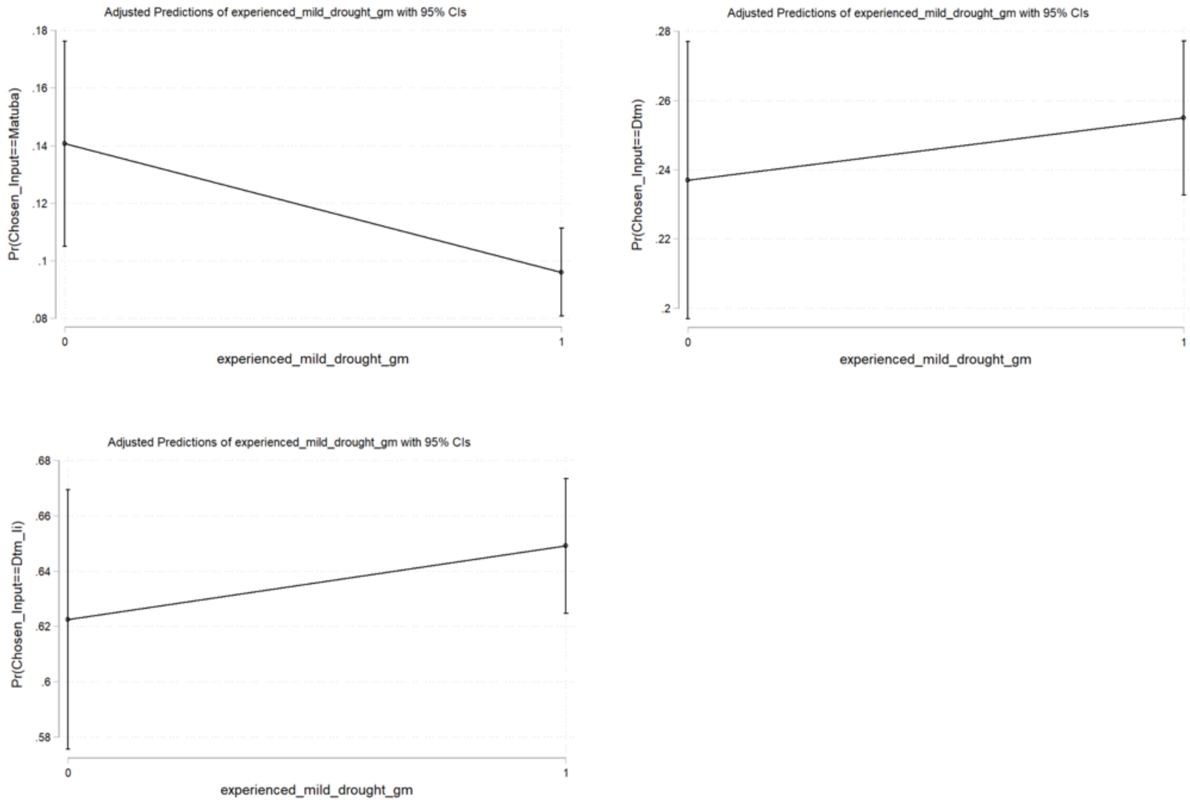

Figure B.2: Average Marginal Effects for Experience with Mild Drought During The Game — Model 2.

- Average marginal effect for MNL model 2 in Table 3.10, for the covariable of whether the farmer had ever experienced a covariate severe drought during the previous round being played:

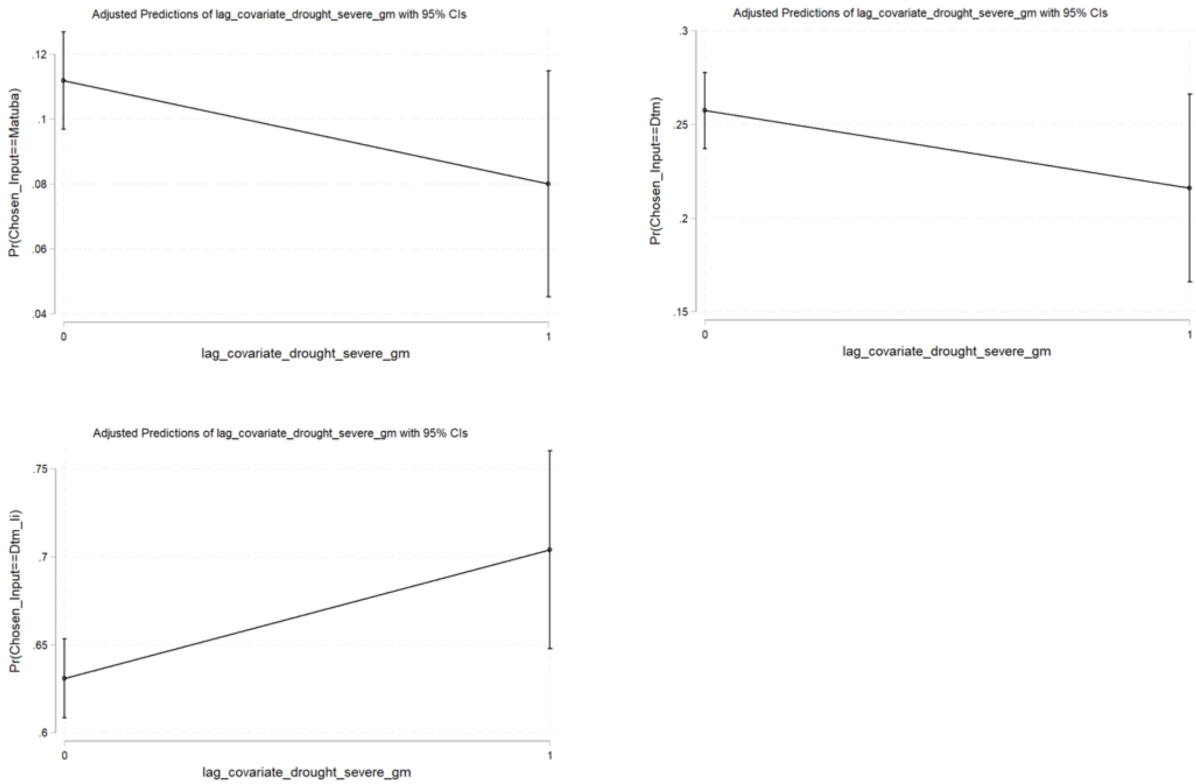

Figure B.3: Average Marginal Effects for Lagged Covariate Severe Drought During The Game — Model 2.

- Marginal effect at representative value interacting real and simulated mild drought - Model 3 (see Table 3.14):

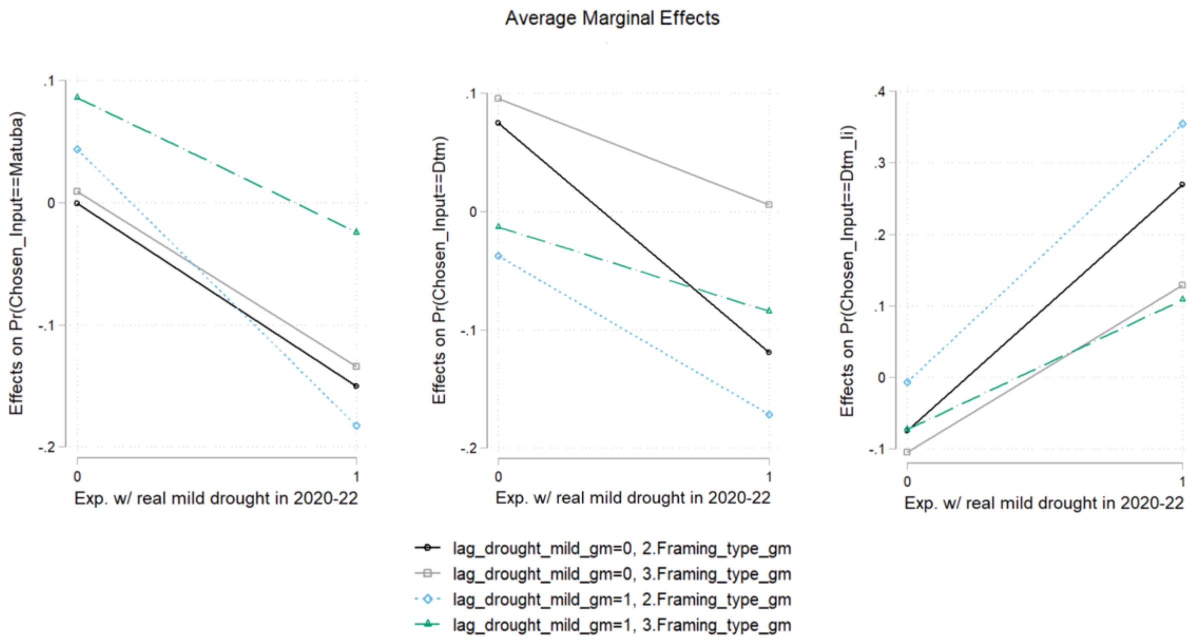

Figure B.4: Marginal Effect at Representative Value Interacting Real and Simulated Mild Drought — Model 3.

- Marginal effect at representative value interacting real and simulated severe drought - Model 3 (see Table 3.15):

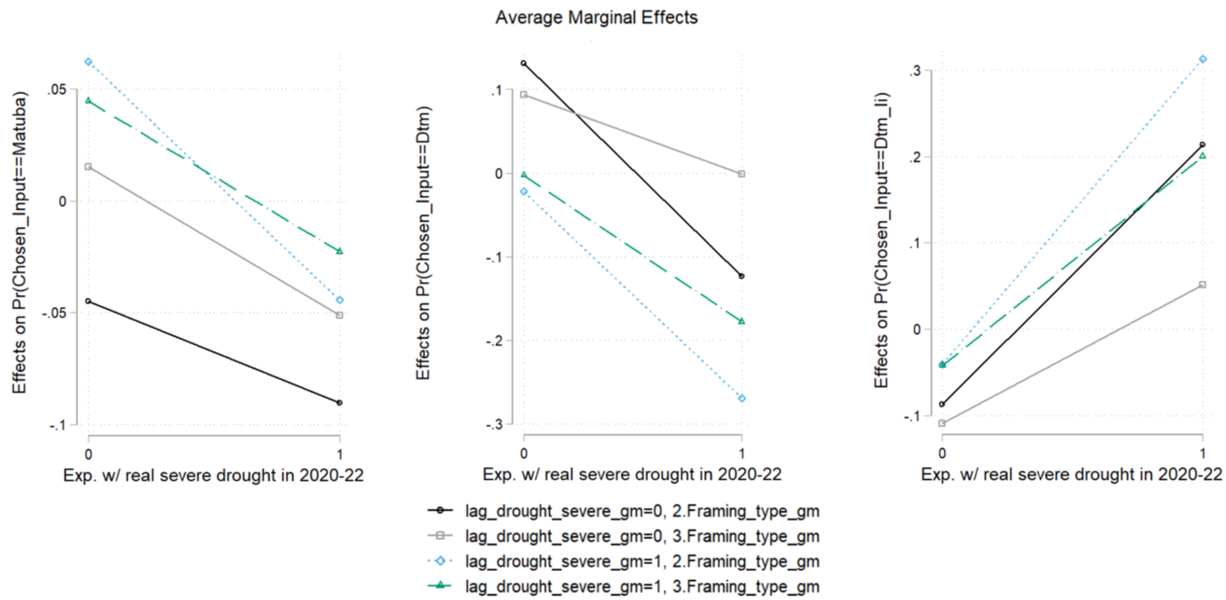

Figure B.5: Marginal Effect at Representative Value Interacting Real and Simulated Severe Drought — Model 3.

B.3 Model selection

With a p-value of 0.1527, we fail to reject the null hypothesis that, as a group, the variables removed in the nested model are statistically different from 0, so including them in the model does not result in a statistical improvement in the model fit (See Table B.2).

Table B.2: H2: Likelihood Ratio Test for Model Comparison.

Likelihood-ratio test	LR chi2(10) = 14.47
(Assumption: $H2\_nested1\_MNL1$ nested in $H2\_super\_MNL1$)	Prob > chi2 = 0.1527

BIOGRAPHY OF THE AUTHOR

Ana María Ospina Tobar was born in Cali, Valle del Cauca, Colombia. She graduated from high school from Colegio Santa Mariana de Jesús in Cali, Colombia and from Marrysville High School in Marysville, California, U.S. She graduate in Summer 2017 with a degree in Economics from Universidad del Valle in Cali, Colombia. She worked for three years after graduation. Among her positions, she was an analyst of businesses ecosystem consolidation and later an entrepreneur and innovation advisor for the Chamber of Commerce in Cali (CCC), developing research that promotes business development in Colombia and Latin America. While at CCC, Ana has published two E-books about entrepreneurship: “The skills of the entrepreneur, a key factor for business growth” (2020) and “Innovation Mapping in Valle del Cauca” (2018). She is also a co-author of the article “Discussion from the Jones specific factors model. The entry into force of the free trade agreement between Colombia and the United States and the impacts on the agricultural sector: Advantages for whom?” (2015), published in Revista Nova et Vetera from Universidad del Rosario. After receiving her degree, Ana will be joining the Resource Economics Ph.D. program at the University of Massachusetts Amherst.

Ana María Ospina Tobar is a candidate for the Master of Science degree in Resource Economics and Policy from the University of Maine in August 2023.