Decision-Making under Risk and Uncertainty: Analyzing Farmers' Behavior through Experimental Methods

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by

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CERTIFICATE

(For Ph.D. Dissertations)

This is to certify that the thesis entitled **"Decision-Making under Risk and Uncertainty: Analyzing Farmers' Behavior through Experimental Methods,"** submitted by **Mr. Raghavendra Kushawaha** bearing registration number **16SEPH22** in partial fulfillment of the requirements for the award of **Doctor of Philosophy** in the School of Economics is a bonafide work carried out by him under our supervision and guidance.

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Further, the student has the following publications before submission of the thesis for adjudication and has produced evidence for the same in the form of an acceptance letter or a reprint in the relevant area of his research.

Publications

1. Raghavendra Kushawaha & Naresh Kumar Sharma (2023), Scope of Behavioral Economics in Agricultural Decision-Making**,** International Journal of Science and Research, ISSN No. 2319-7064, Volume 12 Issue 5, May 2023**,** pp. 2479-2484**.**
2. Raghavendra Kushawaha & Naresh Kumar Sharma (2023), Determinants of Risk Behavior among Poor Farmers**,** Empirical Economics Letters, ISSN No. 16818997, Volume 22 Issue 9, Sept 2023, pp. 89-100.

and

has made presentations at the following Conferences:

1. Presented a paper on "Role of Risk and Uncertainty in Seed Adoption: A Cumulative Prospect Theory Approach" at "The Indian Econometric Society' conference organized by the University of Hyderabad
2. Presented a paper on "Cognitive Ability and Risk Aversion: Farmers' Behavioral Response and Well-being" at the 15^{th} Doctoral Thesis Conference organized by ICFAI Business School

3. Presented a paper on "Risk attitude and perception response of MSPs in production decision among Farmers: A Cumulative Prospect Theory Approach" at the 81st Annual Conference of the Indian Society of Agricultural Economics" organized by Shri Mata Vaishno Devi University (SMVDU) Jammu.
4. Received the best paper award entitled "A History of Methodological Perspective of Behavioral Economics" at the fifth annual conference of the Telangana Economic Association (TEA).

Further, the student has passed the following courses towards the fulfillment of the coursework requirement for a Ph.D. was exempted from doing coursework (recommended by the Doctoral Committee) on the basis of the following course passed during his M.Phil. Program and the M.Phil. The degree was awarded:

No.	Course No.	Title	Credits	Pass/Fail
1.	EC701	Advanced Economic Theory	4	Pass
2.	EC702	Social Accounting and Data base	4	Pass
3.	EC703	Research Methodology	4	Pass
4.	EC751	Study Area	4	Pass
5.	EC752	Dissertation	4	Pass

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DECLARATION

I, Raghavendra Kushawaha, hereby declare that this thesis entitled **"Decision-Making under Risk and Uncertainty: Analyzing Farmers' Behavior through Experimental Methods,"** submitted by us under the guidance and supervision of **Prof. Naresh Kumar Sharma**, School of Economics, University of Hyderabad, and Co-supervision of **Dr. Prajna Paramita Mishra**, School of Economics, University of Hyderabad is a bonafide research work. We also declare that it has not been submitted previously in part or in full to this University or any other University or Institution for the award of any degree or diploma.

Date: 17.11.2023

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By

Raghavendra Kushawaha

This thesis is dedicated to my family members for their limitless Support and patience

&

Supervisor Prof. Naresh Kumar Sharma

And

Dr. Prajna Paramita Mishra

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List of Abbreviations

CPT	Cumulative Prospect Theory
HL	Holt and Laury
TCN	Tanaka, Camerer and Nguyen
MSP	Minimum Support Price
BIMARU	Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh
NFSA	National Food Security Act
SRR	Seed Replacement Rate
RDU	Rank Dependent Utility
vNM	von Neumann Morgenstern
BDM	Becker–DeGroot–Marschak
MPL	Multiple Price List
FOSD	First order Stochastic Dominance
SOSD	Second Order Stochastic Dominance
JP	Just and Pope
EUT	Expected Utility Theory
CRRA	Constant Relative Risk Aversion
PRRA	Partial Relative Risk Aversion
IPRA	Increasing Partial Risk Aversion
WEUT	Weighted Expected Utility Theory
CPRA	Constant Partial Risk Aversion
ARA	Absolute Risk Aversion
MPM	Multiple Probit Model
NSSO	National Sample Survey Organization
RA	Risk Aversion
LA	Loss Aversion
PW	Probability Weighting

KCC	Kisan Credit Card
HYV	High Yield Variety
NRRI	National Rice Research Institute

Chapter 1

Introduction

1.1 Background of the Study

Agriculture constitutes a financially uncertain endeavor, especially in developing countries. In these countries, farmers navigate a volatile environment with limited options to cope with. In light of this unpredictability, comprehending farmers' perspectives on risk and their corresponding attitudes becomes pivotal. How farmers respond to specific policy endeavors plays a significant role in determining their future sustenance and destiny. A substantial body of literature exists in scrutinizing farmers' risk perception and attitude. Over time, numerous theoretical and empirical approaches have emerged to examine risk-related conduct. From a theoretical aspect, despite the well-established expected utility model of decision-making, Cumulative Prospect Theory (CPT) is another milestone of behavioral economics that has frequently been used in understanding farmers' decision-making under risk. CPT offers an alternative model accentuating three dimensions of risk-associated human conduct. This methodology became more prevalent in examining various aspects of risky human behavior.

Another methodological aspect involves using experimental approaches for conducting surveys in economic analysis, representing a relatively novel development in the field of economics. The examination of risk behavior through an experimental approach has undergone recent advancement. Notably, Holt & Laury[1] (2002) (HL) method has gained popularity as a means to comprehensively grasp behavioral nuances linked to risky behavior. This study incorporates HL

[1] This is one of the methods of set a of lottery choices, in which, probabilities are set to be systematically defined in an increasing and decreasing order with respective payoffs. The payoffs over each column are constant. Various studies have been analyzing risk behavior using the derived experimental procedure from the HL method.

and Tanaka, Camerer, and Nguyen (2010) (TCN) experimental methods. Tanaka, Camerer, and Nguyen developed the TCN procedure in their study, recently gaining increasing prominence.

This study delves into the decision-making process regarding risky behavior within the context of farmers in Madhya Pradesh. Over the past two decades, Madhya Pradesh has achieved remarkable agricultural growth, boosting an agricultural growth rate of approximately 10 percent. This growth can be attributed to robust infrastructure support and the implementation of a price stabilization policy known as Minimum Support Price (MSP), as highlighted by Gulati et al. (2017). The present study examines the various dimensions of farmers' risk behavior within the framework of agricultural decisions.

The recent trajectory of agricultural growth has transitioned from the most underdeveloped states (Bihar, Madhya Pradesh, Rajasthan, and Uttar Pradesh, often referred to as BIMARU) to defying trends and establishing a model state for agricultural advancement. A comparative analysis of this growth and its implications for the other regions shows that the agricultural Gross Domestic Product (GDP) experienced 8.1% growth from 2005-06 to 2015-16, subsequently accelerating into double-digit in recent years. Notably, Gujarat emerged as the second-fastest growing state with a 6.0%, a significant gap in the agricultural growth rate within the same period. In addition, the per capita income of Madhya Pradesh remains modest, standing at a yearly Rs. 104894 (as of FY 2020-21 at current prices), in contrast to the average annual national income of Rs. 145679.

As of 2018, Madhya Pradesh's estimated population reached 82.3 million, with 54.6% of the population engaged in agricultural activities. The state characterizing its agrarian nature constitutes 47% of its Gross State Domestic Product (GSDP) to the agriculture sector (as of the 2021-22 budget). This indicates that Madhya Pradesh predominantly relies on agriculture and boasts a diverse agro-ecological landscape that accommodates a wide variety of crop production. The state has earned the moniker "Soya State," as it contributes a substantial 60% country's total soya production. Moreover, Madhya Pradesh holds leading positions in producing pulses, oilseeds, and food grains.

Regarding land ownership, the state characterized the prevalence of small and marginal farmers. The agricultural census of 2015-16 revealed that a substantial 75.5% of farmers held land size of less than 5 acres. The average landholding size accounted for 1.57 hectares (equivalent to 3.88 acres).

Leading to agricultural growth and changing cropping patterns, food grains have been the main crop in the state, occupying around 62% of the gross cropped area. Following oilseeds, accounting for 32% a share in 2014-15. Notably, two major crops, wheat and soybean, have witnessed significant expansion in their cultivation areas. Furthermore, the horticulture sector has displayed an upward trajectory, with vegetable cultivation areas expanding from 284000 to 930000 hectares between 2010-11 and 2017-18. This remarkable growth indicates a nearly threefold increase in the share of land dedicated to vegetable cultivation.

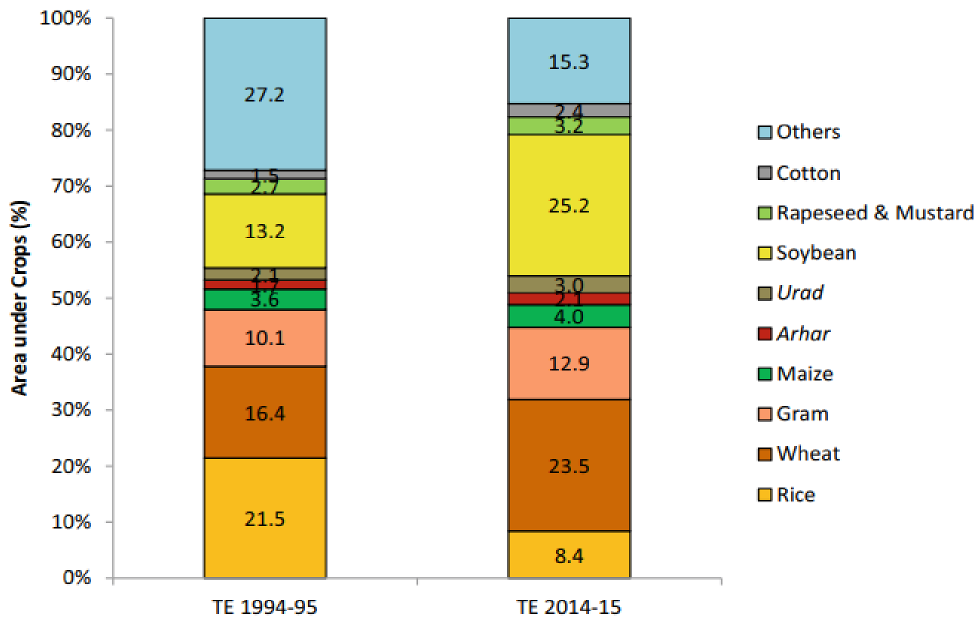

Figure: 1.1 Cropping Pattern in Madhya Pradesh (Source: Directorate of Economic and Statistics, 2018)

Given the rapid evolution of agricultural patterns and the rising trends in agricultural growth, this study concentrates on dissecting farmers' decision-making processes in the presence of risk and uncertainty. It acknowledged that farmers' attitudes towards risk play a pivotal role in shaping production choices in agricultural decisions. Hence, the primary objective of this study is to analyze the determinants of farmers' risk behavior. This analysis involves scrutinizing the impact of various farmers and farm-related characteristics on risk attitudes. Furthermore, the MSP has historically served as a policy instrument declared by the government to mitigate risk in agriculture. Consequently, the present study examines farmers' perceptions of the MSP and its implication on production decisions as risk-mitigating tools.

Similarly, the Seed Replacement Rate (SRR) is essential for progress in the dynamic agricultural environment. Alarmingly, Madhya Pradesh has lagged in terms of seed replacement rates. It was found to be surprisingly lowest compared to other states across the country. This study delves into the role of risk and uncertainty in seed adoption for paddy production, approaching from a behavioral perspective.

1.2 Objectives of the Study

Given these facts, it motivates to specify the objectives of the study:

A. To analyze the determinants of farmers' risk behavior.
B. To study the role of MSP and risk behavior in production decision-making.
C. To analyze the role of risk and uncertainty behavior in the adoption of new seed varieties in paddy production.

1.3 Study Area

This study was conducted in the Rewa district of Madhya Pradesh. It covers 6314 square km of area and is divided into nine blocks, 827 gram-panchayats, and 2352 villages. The district literacy rate was reported to be 71.62% (2011 census), close to the state level of 69.32%. As per the NITI Aayog report (2021) on the multidimensional poverty index (MPI), Madhya Pradesh placed in fourth position (36.65%) in the index at the national level, and Rewa is also close to this index with (37.04%).

Rewa is located in the eastern part of the state, where Paddy and Soyabean are the major crops, but other crops, i.e., wheat, sorghum, pulses, oilseeds, and vegetables, also have a significant share. This study uses convenience sampling and conducted experiments and surveys in three villages Pakara, Chandeh, and Balmukunda, where agriculture was the main source of livelihood. Further, the respective chapters in the studies describe detailed descriptions of the data.

Figure: 1.2 Location of District (Rewa) Study in Madhya Pradesh

1.4 Chapter Outline

The present study, chapter 1 is an introduction to the study, Chapter 2 consists of a literature review in which we have tried to cover all relevant previous studies. It finds that the prospect theory has been extensively used in various contexts in understanding risk behavior. In recent times, there has been rich literature on understanding the farmers' risk behavior, in general, and extensive use of experimental methods in eliciting risk behavior across the countries. Most of the studies use experimental methods applying HL and modified HL method, emphasizing the subjective probability and perception framework of various risk attitudes in different countries. However, some studies exhibit extreme risk aversion behavior among poor countries (Liebenehm & Waibel, 2014). We find that farmers in developed countries are more risk-averse than farmers in developing countries. We also find various studies in the context of Indian farmers, and more specifically, Binswanger (1980, 1981) was perhaps among the first studies that tried to examine the farmers' risk behavior. This study was a motivating point that helped proceed with the experimental approach in analyzing farmers' risky behavior. Further, the major arguments on the asset integration model and wealth effect have also been discussed, reflecting that behavioral economics and the experimental method significantly contribute to understanding risk behavior.

In Chapter 3, we examined the determinants of risk behavior among farmers in Madhya Pradesh. We used the expected utility and prospect theory model in the analysis and the HL experimental procedure to elicit risk preference. We found that both models are significant in explaining the risk behavior. However, prospect theory provides a broader view of understanding risky behavior. It can be said that undermining the prospect theory can miss an important behavioral characteristics in the model. The study found significant behavioral characteristics of probability distortion among farmers.

In Chapter 4, we analyzed the role of risk behavior in response to the Minimum Support Price (MSP) in the production decision. In a limited option of risk reduction strategy among Indian farmers, MSP has been one of the essential risk-mitigating tools, and it provides an option to reduce the price risk. MSP is the minimum support price the government of India announces before crops come into the market. The government also procures wheat, rice, and other items directly from the farmers under the National Food Security Act 2013 (NFSA) to ensure access to adequate food at an affordable price for people in poverty. Therefore, farmers can choose such items that come under MSP. We consider that risk attitude is an essential factor in decision-making. If a farmer's behavior is highly risk-averse, he may prefer less risky options in production decisions, such as MSP crop items, in the production decisions. This study uses the TCN experimental procedure and prospect theory model to capture farmers' risk attitude characteristics, i.e., risk aversion, loss aversion, and probability weighting. The result highlighted significant behavioral characteristics and are statistically significant in determining the adoption of MSP crop items.

In Chapter 5, the study analyzes farmers' behavior under risk and uncertainty in the framework of prospect theory with experimental procedures to analyze the seed diversity and adoption of new seed varieties in paddy production. As we know, rice is one of the major crops of India and the backbone of the livelihood of millions population. The issue of adopting new seed varieties is crucial, and it is directly linked to sustainability and food security. Seed adoption among Indian farmers is very much informal. Due to higher seed price, and information gaps in seed quality, farmers mostly favor home-saved seeds for the next cropping season. Adopting a new variety into existing ones is a continuous process, and it progresses with time lag through trial and error. As for the Ministry of Agriculture GoI report, Madhya Pradesh posits least in India's seed replacement rates (SRR) list[2]. The seed replacement rate is a percentage of the area sown to new seed out of the total area of the crop planted in the next season. It must be certified/quality seeds other than saved seeds from the previous year. It is considered that farmers' risk behavior is associated with the adoption of new seed varieties. A highly risk-averse farmer generally hesitates to include new varieties of crops in the production basket due to the information gap. We analyze the role of risk and uncertainty in adopting new seed varieties in paddy production. The study finds that farmers adopt new seed varieties as a risk-mitigating strategy. We also found a low adoption rate of new seed varieties caused by farmers' hesitation to take more risks.

Besides following the goals of this thesis, this study also covers the methodological aspects of experimental procedures derived from the famous HL Procedures. The derived HL procedures have been frequently used in risk elicitation procedures in various studies. Various studies have derived experimental procedures based on the HL methods (Senapati, 2020; de Brauw & Eozenou, 2014; Hellerstein et al., 2013; Menapace et al., 2013; Cardenas et al., 2013; Cerroni, 2020). All these studies have tried to simplify it so that experimental procedures could capture the true value of individual behavior from developing countries where respondents are less educated or unable to read and write. In this study, all experiments were conducted in the same region with homogeneous socio-economic backgrounds; therefore, we can compare the original HL procedure (Chapter 3) and the most commonly used derived experimental procedure in various studies (TCN) (Chapter 4). The experimental procedure in Chapter 5 is also a TCN procedure, and Ward & Singh (2015) have modified making an option choice constant in the experiment. Therefore, there is a possibility of certainty effect in the decision-making.

[2] As for 2011 data, seed replacement in the paddy production in Madhya Pradesh is only 16.85 whereas Andhra Pradesh hold top position with 87.21.

Chapter 2

Literature Review

2.1 Introduction

Despite the rapid decline in the share of agriculture in GDP and the structural changes in the national income in developing countries, agriculture is still an essential part of their growth and development (Diao et al., 2010; Loizou et al., 2019). Favorable agricultural growth positively influences the well-being of farmers in developing countries and also acts as a shock absorber in tough times (Bahta et al., 2014).

Agriculture is inherently considered a relatively risky business due to the nature of its production (Moschini & Hennessy, 2001; Hardaker et al., 2004; Akcaoz & Ozkan, 2005; Ullah et al., 2016). Agricultural risk comes from various sources, primarily the natural environment and climatic characteristics, causing farmers to be exposed to higher risks (Ullah et al., 2016; Moschini & Hennessy, 2001). Farmers in developing countries generally face higher risk exposure than those in developed countries (Akcaoz & Ozkan, 2005).

Farmers' behavioral response is critical in risky decision-making (Ullah et al., 2016). Various studies have witnessed different risk exposures, varied responses at different locations and found substantial differences in risk management strategies (Akcaoz & Ozkan, 2005; Cardenas & Carpenter, 2013; Vieider et al., 2019;). In this regard, it becomes critical to understand how they make risky choices that might reflect on their well-being (Lowenberg-DeBoer, 2015). Behavioral factors become vital in understanding the farmers' risk attitude and risk perception in a broader policy domain (Ullah et al., 2016). Various studies have included behavioral factors to model risk behavior (Bellemare et al., 2020; Smith & Mandac, 1995; Turvey et al., 2013; Fu et al., 2022). For example, a general perception is that farmers are naturally risk-averse (Dillon & Scandizz, 1978; Binswanger, 1980; Anderson et al., 1977; Liu, 2012). However, there is also evidence that sometimes, farmers dare to take relatively unconventionally higher risks (Just & Lybbert, 2009; Maertens et al., 2014; Ross et al., 2012).

Farmers' decision-making in the presence of risk is complex (Hardaker et al., 2004; Just & Pope, 2003). Many such risks, like production risk, credit risk, market risk, environmental risk, and institutional risk, have been the subjects of numerous studies (Maertens et al., 2014; Senapati, 2020; Zhao & Yue, 2020; Bellemare et al., 2020; Ward & Singh). Analysis in the earlier studies on farmers' risk behavior has essentially been based on the expected utility models of decision-making (Just & Peterson, 2010). However, many studies contend that the method is unfavorable. (Bellemare et al., 2020). Recent theoretical advancements provide alternative methods that have evolved simultaneously to understand an individual's risk-taking behavior. The studies incorporating these models assume that probabilities are not uniformly linear and decision-maker's sensitivity varies in the risk and loss domain.

Just & Lybbert (2009)[3] analyzed farmers' risk-taking behavior and tried to measure standard and marginal risk aversion in their experimental study. 'Marginal risk aversion' was defined as a comparison between gambles presented to the respondents to assess behavioral change in the decision while changes occur in the gamble. A better alternative to analyze such risk aversion is given by Holt & Laury (2002), which provides a more comprehensive systematic method to capture individual behavior at different levels of risk exposure.

At the macro level, systematic risk in the agricultural business is analyzed through various methods, especially in the developed world. It is a method of analyzing the macro variables in aggregation in investment decisions in farm enterprises (Bernard et al., 2021). Systematic risk management is important in understanding the complexity of risky activities. However, such estimation of systematic risk is less utilized in the farm business that considers agricultural risk

[3] This study followed an experimental method consisting a series of prospective seed varieties of high, medium and low risks with respective returns to analyze farmers responses in given risk exposures. This study concluded that marginal risk aversion does not explain the measure of standard risk aversion behavior. This study was conducted in Tamil Nadu state in India (see Just & Lybbert, 2009).

too complex (Leppälä et al., 2015)[4]. Due to its peculiarity, different levels of risks are associated at various points during the production decisions, and it varies according to farm assets management and given risk exposure.

Hardaker et al. (2004) emphasized that incomplete information causes decision complexity, and quantifying systematic risk estimation in agriculture is challenging. Additionally, it contended that farm-related risks are very much individualistic. Individual farm management strategies for identifying, categorizing, evaluating, and prioritizing their objectives and associated risks are peculiar (Willock. 1999).

In developing countries, production decisions can be characterized as based on small-scale production with resource constraints and high dependence on informal sources of information. Farmers do not have a well-structured managerial unit as typical firms do, which would enable them to make precise strategic decisions, i.e., predict climatic conditions, predict prices, negotiate contracts, and manage input variability and other risk factors. They generally make their decisions by consultation with friends, families, personal experiences, skills, and intuition. However, a risk management strategy is a crucial part of sustainability in a farming business. While making decisions on crop selection and input selection under risk and uncertainty, farmers generally lack expert advice and rely on informal sources of information, viz., self-intuition, peer opinion, and past experiences. In such cases, a subjective probability model is presumably more effective for analyzing risk and uncertainty behavior. Ample literature and empirical work on subjective probability have evolved in the last forty years. Such literature on behavioral factors in decision-making helps us understand the cause, consequences, and complexity of risks faced by farmers.

Against this backdrop, the present chapter primarily focuses on reviewing the methods of the experimental approach and the use of prospect theory in analyzing risk behavior among farmers. Recent developments in the experimental approach complement alternative theories and provide a new dimension to analyze risky behavior, especially after the introduction of the HL method. This approach is based on the notion that farmers' subjective probability drives utility maximization in

[4] J. Leppala emphasize that the role of administration is crucial in management of agricultural risks associated with various levels in agricultural practices i.e., starting it from crop selection then production risk, agro-climatic risk and market risk. At each stage it needs an independent and scientific methods for specific risk mitigation strategy.

the decision analysis. This method has been extensively used in analyzing production, climatic, input, and market risks in the past decade. This experimental method is also considered more efficient because it gives decision-makers more flexibility to capture subjectivity and intuition in risky behavior.

A clear comprehension of risk behavior among farmers is crucial for government agencies and policy-makers in implementing various risk-reducing policies. Therefore, understanding the farmers' perception and attitude toward risk under various risk exposures and their responses during the production decisions is essential for policy effectiveness.

Further, this approach has potential significance in the policy analysis of risk mitigation strategies. Over the years, agricultural economists have continuously focused on analyzing farmers' responses to various sources of risk exposure and responses to risk-mitigating tools. This new paradigm of modeling and prediction in response to the risky environment got adequate attention in farmers' decision-making processes. This is a normative model of risky decision analysis based on the assumption that individual beliefs reflect in the decomposition of some important decision problem.

Various empirical studies have applied prospect theory in the analysis of risk behavior. (Zhao & Yue, 2020; Cerroni, 2020; Gonzalez-Ramirez et al., 2018; Moser & Mußhoff, 2017; Schaak et al., 2017; Bougherara et al., 2017; Bocquého et al., 2014; de Brauw & Eozenou, 2014) The HL experimental method has also frequently been found to analyze these studies, primarily considering the theoretical background of prospect theory. The following sections briefly discuss the literature on farmers' risky behavior, focusing on this alternative experimental method.

2.2 Risk Behavior and Wealth Effect

The debate surrounding individual risk behavior and the role of potential assets is still open for discussion. The nature of wealth is broadly differentiated in wealth and income and its implication in determining risk behavior. The expected utility theory is the dominant approach in evaluating decisions under risk and uncertainty. The most prominent discussion revolves around individual consumption level as a function of final wealth, which is directly associated with the potential changes in wealth in terms of gains and losses. Individual assets in terms of income and wealth on risk behavior assume full integration of income from all sources of investment decisions.

Markowitz (1952) and Anderson et al. (1977) highlighted the income approach and pointed out that changes in gains and losses are the key to changes in risk behavior.

Binswanger (1980; 1981) worked on studying farmers' risk behavior through an experimental approach; since then, numerous studies have been carried out using experimental approaches in different contexts to assess risk in agricultural decisions. Binswanger (1980), in his study on Indian farmers, analyzed the differences in farmers' risk behavior and its determinants using the expected utility framework. Further, he critically analyzed the expected utility framework and methods and pointed out the role of wealth and income effect and stakes of a farmer in decision-making (Binswanger 1981). His study was based on subsistence farmers and concluded that farmers' risk behavior could be explained through partial risk aversion at lower stakes.

Later, scrutiny of the expected utility framework led to a more generalized model of risky behavior. Kahneman & Tversky (1979), Machina (1982), and Quiggin (1982) proposed alternative models, assuming weight-assigned outcomes in the preference relation are not linear. Machina (1982) proposed a generalized model of expected utility, a non-linear differentiable utility function over final wealth distributions. He showed that differentiability in the utility curve of "local linearity" properties of preferences carries over to a global preference. It is evaluated in terms of the expectation of a given "local utility function" derived from the distribution of the final wealth of the current prospect.

The advantage of asset formulation in evaluating the effect of asset changes on individual behavior is that it changes the nature of utility function as wealth level changes. Measuring the utility after asset changes is also crucial because different kinds of assets, i.e., land, machinery, cash, incentives, etc., are not perfectly substitutable. In this context, it becomes more crucial and is less explored in understanding the farmer’s risky behavior under constrained resources.

The empirical estimate of risk attitudes has been drawn, assuming that the utility function will remain stable over gains and losses. However, Binswanger's experimental study that presented a gamble over a relatively small probability with high stakes found that respondents frequently turned down their decision towards moderate risk aversion behavior. This changing behavior has been analyzed in the model of non-linear probability transformation, and calibration critique became a strong foundation in behavioral economics. Income or wealth is not the sole driving factor in the decision, and income is no longer fully integrated with wealth to explain risk aversion behavior (Heinemann, 2005). Moreover, Binswanger also broadly concluded from his study that 1) risk aversion behavior is widely distributed from the intermediate level of risk to neutrality at very low payoff levels. 2) Risk aversion parameter shifted towards the intermediate and moderate levels at moderate stakes. 3) Wealth does not appear to influence risk aversion at higher stakes, but such an effect appears to exist at low stakes.

Following the above conclusions, it could be interpreted that the argument of the utility function with prospects to follow different patterns varies for smaller and higher stakes in the gamble. However, a Zambian study based on a similar experimental approach found contrary results (Wik M. et al., 2004). With increasing stacks in the game in terms of payoffs, the study concluded that 80 percent of decision-makers shifted towards extreme risk aversion behavior, and wealth negatively correlated with risk aversion. These results were yet again contrasted by another study (Mosley & Verschoor, 2005) which analyzed cross-country (Uganda, Ethiopia, and India) risk behavior and concluded that risk aversion has little correlation with income and a strong relationship between wealth and return. Rabin (2000) argued his famous calibration paradox considering the terminal wealth in the utility function and made a similar conclusion. Given these studies, it is concluded that a uniform utility function of risk aversion for higher stakes and lower stakes is not plausible under the terminal wealth specification. In other words, the expected utility model assumes that a utility function represents preferences over prospects as Σ_i u(p_i) v(w_i), in which probabilities p_i are considered to be linear coefficients in the vNM model to any level of final wealth is not always appropriate.

Kahneman and Tversky's proposition of the asset integration model considers wealth and income to be the same and infers weight over the change in final prospect in terms of probabilities and utility index define the preference function Σ_i u(p_i) u(w_i). This model assumes that probabilities are not uniformly linear. Further, in a recent study of the Danish population, choice over lottery prizes was found to be inconsistent with personal wealth. (Andersen et al., 2018)[5]. In order to explain individual risky behavior with experimental prizes of a utility function, only a fraction of wealth was found to be associated with the experimental payoff. The study concluded that partial

[5] This study was conducted with detailed information of individual wealth data taken from Statistics Denmark and experimental data of risk attitudes in a given choices followed by Harrison & Rutström E., (2008).

asset integration exists and that a fraction of wealth cannot be perfectly substituted with total wealth. In this paper, the author also applied the alternative rank-dependent utility (RDU) model, which concluded that behavior is characterized by diminishing marginal utility under partial asset integration. In another study in the context of subsistence farmers in Paraguay, self-reported daily incomes and lottery choices were consistent with the full assets integrated model of expected utility (Schechter, 2007). The study used consumption data to replace wealth, which concluded that relative risk aversion is substantially higher. Further, it also concluded that these farmers in experimental payoffs at a higher stake reflected deviation in the result and accounted for one-fourth of the coefficient compared with farmers with the capacity to save.

In general, wealth and income characterization of risk aversion is not the same (Cox & Sadiraj, 2006). It is essential to know how farmers integrate their potential income with wealth in decision-making under risks. Experimental procedures have recently evolved to analyze risk aversion behavior with income and assets (wealth, human capital, financial assets). Most studies have concluded that partial asset integration is similar to earlier studies (Binswanger, 1980; Schechter, 2007; Andersen et al., 2018; Heinemann, 2005). However, in an alternative model, subjectivity was also found to be a crucial factor in the decision-making that behavioral economists emphasized.

Finally, it is implausible to assume that farmers put all their stakes at risk when working at higher risk at the subsistence level. In an agricultural production system, farmers primarily make decisions at higher stakes risk (Hardaker et al. 2004); they work in an environment where it is hard to assess probabilities and respective outcomes. In the developing world, agriculture entails more uncertainty than other industries. Therefore, many authors proposed a safety-based rule of thumb to describe and predict farmers' risky behavior, especially in developing countries. However, the recent development of different models of nonlinear parameters, i.e., rank-dependent utility theory (Quiggin, 1982) and cumulative prospect theory (Tversky & Kahneman, 1992), have been well developed to explain such risky behavioral phenomena.

2.3 Subjective Expected Utility and Probabilistic Belief

Recent literature in decision-making under risk and uncertainty has evolved in a direction that emphasizes the role of cognition as a vital and independent individual trait. It affects reasoning, accounting, and motivation and is intrinsically responsible for the decision process. Kahneman's idea of cognition[6] in behavioral economics has often appeared where individual intuition, biases, and framing are known as behavioral traits. It has been used frequently and has become a widespread term in economic literature in recent years. These variables suggest a nonlinear characteristic of the utility function, where the underlying idea is that the economic actors' behavior is not always monotonous.

Subjectivity in risk analysis, eliciting the probability and their use in decision-making, has a long history. de Finetti (1972) argument, as cited by Feduzi et al. (2014), explained the subjective nature of probability as expressing the notion of an individual degree of belief regarding the occurrence of an event given the level of information available. It means that subjective probability may vary individually for the same event if they have a different level of information or interpret the same information differently.

Furthermore, the subjective probability was also interpreted as "potential surprise" by Shackle (1952), as cited by Basili, M., & Zappia, C. (2010), where he described that individual experience and learning about a particular event occurrence would influence the individual's probable decisions. Ramsey (1926), as cited in MacBride et al. (2019), proposed subjective probability in terms of "degree of belief" that characterized probabilistic sophistication and emphasized the necessity of having a psychological measurement method. Further, Savage (1954), Anscombe & Aumann's (1963) argument, as cited by Karni, 1999), emphasizes subjective probability, which is differentiated from objective probability in certain circumstances.

To account for the preferences in the process risk or uncertainty, a potential degree of belief of an event must exert in the behavior and methods of estimating subjective beliefs drawn from the assumption of a subjective probability distribution[7]. In the case of an uncertain event, precision in subjective probability derives from the knowledge that affects preference directly. Lack of

[6] Kahneman described the mental process in decision-making. He criticized the rational model of judgment and decision-making and described the decision-making process through the lens of psychology. He argued that the brain works in two different setups, system 1 and system 2. System 1 is automatic and impulsive which drives the fast, intuitive, and effortless decision-making whereas system 2 is deliberative, slow, and effortful in the decision making (see. Thinking Fast and Slow).

[7] Andersen et al., (2012) tried to estimate subjective belief in terms of subjective probability distribution through a well-defined experimental task, it was found that physical stimuli do not affect the probability distribution.

information and intuition subjectively perceived from events suffer from precision, which might reflect risk behavior (Fountas et al., 2006). A review paper found a deeper understanding of subject-specific characteristics and varying degrees of estimated risk aversion reflected in economic decisions (Hardaker & Lien 2010). Individual cognitive ability has also been taken as a determinant independently and associated with risk aversion (Dohmen et al., 2018)[8]. In an informal setting of decision-making, individuals are not precisely aware of events and their chances; their decisions primarily based upon subjective beliefs that might vary individually and not necessarily correspond with actual value. In this case, the underlying cognitive processes, heuristics, and individual specification, particularly shaping subjective belief in a complex setting, are essential to understand.

The subjective probability has attracted some attention, especially in agricultural decisions (Hardaker & Lien, 2010). Some empirical studies in agriculture witnessed that subjective probabilities are crucial in understanding decisions such as crop diversification (Ouattara et al., 2019), climatic risks (Kunreuther et al., 2013), insurance selection (Coble et al., 2004; Shaik et al., 2008) and the response of various agricultural policy designs. This indicates that the subjective notion of risk or uncertainty, based on individual intuition and psychology, is also a critical determinant in decision-making (Mani et al., 2013).

A common method in decision-making analysis is to ask farmers directly about the likelihood of events, which is known as a subjective probability in decision-making. It is pronounced among theorists that subjective probability can be observable if subjective probabilities describe as a set of mutually exclusive events. Several studies have developed a procedure to recover subjective probabilities, in which latent probability can be found through calibration adjustments mechanism to elicit risk attitude and subjective probability (Andersen et al., 2006; Andersen et al., 2014; Di Girolamo et al., 2015). The calibration adjustment process allows eliciting individual beliefs such as nonlinear utility functions or probability weighting. It infers that subjective probability is conditional to known references from earlier events. When considering priory information, statistical or behavioral uncertainty is updated in the subjective probability. This estimation

[8] Recent studies of decision making suggest that cognitive capability of individual is important in understanding of complex choices. Kahneman (2012) also tried to reveal the role of cognitive limitation and its functioning in the decision (see. Thinking Fast and Slow, 2012).

process suggests that observed probability is not precise but provides a useful empirical understanding of the real world.

2.4 Elicitation of Subjective Probability in Agricultural Decision-Making

Farmers' attitudes toward risk and uncertainty are essential for understanding agricultural decisions (Just, 2003; Chavas et al., 2010). This means it is crucial to understand how decision-makers respond in the presence of risk, as it is typically observed in their behavior in the field. A precise understanding of risk preferences in a specific field environment is crucial. Farmers have substantive experiences and motivations, form their beliefs, and set goals to make predictions. Their attitude towards risk and uncertainty regarding yield, prices, and agroecological conditions is frequently speculated during production decision-making. Farmers mostly work in an uncertain or ambiguous environment where they have limited information[9]; therefore, it is hard to quantify these probabilities (Moschini & Hennessy, 2001). Analyzing uncertainty is generally presumed to be a risky event. In developing countries, farmers have an informal way of making decisions; they generally form their beliefs based on prior information, experiences, and intuition. They form their subjective belief on the likelihood of events.

A small fraction of extensive literature in agricultural economics incorporates subjective probability to analyze the farmers' risk and uncertainty assessment in various contexts (Grisley & Kellog, 1987; Pease, 1992; Pease et al., 1993; Smith Mandac, 1995; Egelkraut et al., 2006;). These studies used various techniques to assess farmer perception and compared it with the probability or cumulative distribution functions. To measure the accuracy and consistency of production decisions in technologies, yields, price, and responses, they tried to observe the subjective distribution and compare it with the distribution of historical data for each farm. A detailed review by Norris & Kramer (1990) of subjective probability and preference analysis of farmers in agricultural decision-making substantiated that the probability density and cumulative distribution functions are not applicable in every aspect.

[9] Precision farming is a concept of reducing risk and variability in the agricultural management decision. It is specifically focused on enhancing the technological advancement, automation and big data analysis to make accurate farming prediction (Lowenberg , 2015)

An alternative approach of measuring risk aversion, designing an experiment, and intervening through the direct use of input commodities in the production decision became popular (Just & Lybbert, 2012; Pease et al. (1993) analyzed farm-level differences, statistical forecasting, and farmers' subjective expectations in their study. They found simple cognitive procedures to estimate yield and other decisions essential to policy design. Likewise, in another popular method of modeling risk aversion, a stochastic dominance-based approach commonly utilizes observing risk attitude estimates based on first-order and second-order stochastic dominance[10] (Maertens et al., 2014; Ranganathan et al., 2018). These studies need time and resources to have the event recurring again and again.

Recently, rigorous and flexible methods have evolved in eliciting risk attitudes. HL consider an efficient method for capturing a more flexible parameterization in the utility function. This subjective probability elicitation method has also been used in agricultural decision-making in various forms. It has become a prominent method after the experimental approach in the economic inquiry became acceptable as it captures a broader picture of individual perception and nonlinear probability function. In more recent times, this experimental method has been applied in various studies regarding farmers' temporal risk behavior (Maart-Noelck & Musshoff, 2013), past experiences, uncertainty behavior (Tonsor, 2018), diversification analysis (Schaak et al., 2017), input risk analysis (Liu & Huang, 2013; Moser & Musshoff, 2017), production risk (Vollmer et al., 2017). These studies are summarized in Table 2.1.

Subjective probability is also accounted for in other methods. Shaik et al. (2008) used a multiple logit model to analyze the demand for crop insurance premiums in the USA farm industry. Studies to analyze the effectiveness of policy response to the demand for crop insurance in the USA farm industry (Coble et al., 1999; Knight & Coble, 1997; Serra et al., 2003) substantiated that individual risk attitudes varied with the level of risk exposure and their risk perception. Varied risk exposure drives the individual subjective probability for the level of information that provides a better explanation for a limited demand for crop insurance.

[10] The Idea of stochastic dominance of utility maximization is defined in terms of the ordering of functions of cumulative distribution. To define first order stochastic dominance (FOSD), suppose A and B are two lottery sets where decision-maker prefers lottery A to B if u(A) is weakly increasing over u(B) or every payoff of lottery A is as good as lottery B; whereas, second order stochastic dominance (SOSD) is defined if decision-maker prefers A to B, if it follow FOSD and he is risk averse or at least one payoff of lottery A is better than lottery B, see (Rothschild & Stiglitz, 1970 ,1971) .

Finally, studies focus on factors influencing risk related to farmers and farm characteristics. Vollmer et al. (2017) used the HL method to design the task to provide an incentive scheme for farmers whose production decisions are obtained from the panel data set. With this data-generating process to investigate the production risk, this study utilizes the Just and Pope (JP) production function (1978)[11]. It is a stochastic production function model in which a farmer's risk attitude derives from the panel data set of the Holt & Laury procedure. This study found that the HL method appropriately elicited the production risk.

Similarly, Moser & Musshoff (2017) study the risk influencing production inputs and its effect on the output. This similar experiment elicits Indonesian rubber farmers' risk behavior with the given JP production function. This study considered fertilizer a major risk-reducing production input factor, whereas herbicides were a risk-increasing production input. Applying the HL experimental method found a consistent relationship between input use and its influences on output risk.

2.5 Farmers' Risk Behavior

This section reports and analyzes some of the prominent literature from across the globe on farmers' risk attitudes, preferences, and behavior and the related risk management strategies they employ to overcome the barriers in agriculture.

Bergfjord (2009) analyzed the risk attitude and role of risk management tools among Norwegian fish farmers. He found that price fluctuation and market access are among the most important sources of risks perceived by respondents. Further, cost reduction and disease prevention were important factors to emphasize to perceive risk management. It also found that economy of scale is important in determining risk management strategies, i.e., more resources lead to more sophistication in risk management strategies.

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[11] The Just and Pope production function has the following model $y_{it} = f(x_{it}, \alpha) + u_{it} = f(x_{it}, \alpha) + \varepsilon_{it}\, h(z_{it}, \beta)^{1/2}$, where y_{it} is per hectare production output of a farm *i* in year *t*, and $f(x_{it}, \alpha)$ is determinants of production function in which x_{it} represents the input factors per hectare of a farm *i* in year *t*, α represents the vector of a technology parameter, and u_{it} represent the heteroscedastic error term which is equivalent to the $\varepsilon_{it}\,(h(z_{it}, \beta))^{1/2}$, this represents the stochastic component of the production function, in which, the relationship between the level of inputs and the output variance where ε_{it} is standard normal distribution $E(\varepsilon_{it}) = 0$ and $var(\varepsilon_{it}) = \sigma_{\varepsilon it} > 0$. Further, β represents vector of technology parameter and z_{it} explains output variance.

Table: 2.1 *List of Studies of Traditional Experimental Approach to Farmers' Risk Preference and Perception Framework*

No	Study	Country	Lottery Type	Perception Framework	Utility Function	Probability Weighting
1	(Dillon & Scandizzo, 1978)	Brazil	Certainty equivalent	EUT	CRRA	Linear
2	(Binswanger, 1980)	India	Binswanger model	EUT	CRRA	Linear
3	(Grisley & Kellog, 1987)	Thailand	Binswanger model	EUT	PRRA	Linear
4	(Belaid & Miller, 1987)	Algeria	Binswanger model	EUT	IPRA CPRA	Linear
5	(Miyata, 2003)	Indonesia	Binswanger model	EUT	CRRA	Linear
6	(Wik et al., 2004)	Zambia	Binswanger model	EUT	CRRA	Linear
7	(Humphrey & Verschoor, 2004a)	Uganda	Random lottery	EUT WEUT	---------	Linear and Nonlinear
8	(Lybbert, 2006)	India	BDM model (Input seeds)	EUT	---------	Linear
9	(D. R. Just & Lybbert, 2009)	India	BDM model (Input Seed)	EUT	CRRA	Linear
10	(D. R. Just & Lybbert, 2012)	India Morocco	BDM Model (Input Seeds)	EUT	ARA and MRA	linear

Continued……….

11	Yesuf & Bluffstone, 2009)	Ethiopia	Binswanger Model	EUT	CRRA	Linear
12	(Asravor, 2019)	Ghana	Binswanger Model	EUT	CRRA	Linear
13	(Ragnganathan et. al., 2018)	India	Stochastic Dominance Method using seed input	EUT	Stoch Domn	Linear
14	(Maertens et al., 2014)	India	Stochastic Dominance method using seed input	EUT	Stoch Domn	Linear

Table: 2.2 *List of the Studies of New Experimental Method of Farmers' Risk Preference and Perception Framework*

No.	Study	Country	Lottery Type	Perception Framework	Utility Function	Probability Weighting
1	(Galarza, 2009)	Rural household (Peru)	HL	EUT CPT	CRRA	Tversky and Kahneman model
2	(Nguyen & Leung, 2009)	Fisherman Attitudes (Vietnam)	TCN	PT	CRRA	Prelec
3	(Tanaka et al., 2010)	Rural Household (Vietnam)	TCN	EUT CPT	CRRA	Prelec
4	(Lucas & Pabuayon, 2011)	Philippine Farmers	HL	WEUT	CRRA	Non-linear
5	(Reynaud & Couture, 2012)	Comparing two elicitation method (France)	HL	EUT PT	CRRA	---------
6	(Liu, 2012)	Risk Preference and tech. adoption (China)	TCN	PT	---------	Prelec
7	(Ross et al., 2012)	Risk and Ambiguity preference and tech. adoption (Laos)	HL	EUT	--------	---------

Continued……..

8	(Menapace et al., 2013)	Risk management strategy (Italy)	HL	EUT	CRRA	----------
9	(Liu & Huang, 2013)	Input (Pesticide use) China	TCN	Cobb-Douglas	No Restriction	Prelec
10	(Hellerstein et al., 2013)	Predictive power of Risk pref. (USA)	HL	PRA	CRRA	Linear
11	(de Brauw & Eozenou, 2014)	Technology adoption (Mozambique)	HL	EUT RDU	CRRA, PRA**	Tversky and Kahneman Model
12	(Barham et al., 2014)	Technology adoption (USA)	HL	Maxmin expected utility model	CRRA	Linear
13	(Bocquého et al., 2014)	General decisions (France)	TCN	EUT CPT	Exponential Power	Prelec
14	(Ward & Singh, 2015)	Technology adoption (India)	TCN	PT	----------	Prelec
15	(Bougherara et al., 2017)	Farmers risk & uncertainty (France)	TCN	EUT CPT SOM*	CRRA	Tversky and Kahneman and Prelec model
16	(Schaak et al., 2017)	Farm diversification (Germany)	HL	EUT	----------	-----------

Continued……

17	(Moser & Mußhoff, 2017)	Risk influencing production input use (Indonesia	HL	-----------	J-P Produc. Function	-----------
18	(Gonzalez-Ramirez et al., 2018)	Sustainable Practices (Argentina	HL	EUT PT	____________	Tversky and Kahneman and Prelec Model
19	(Ihli et al., 2018)	Investment Behavior among Coffee farmers (Uganda)	HL	EUT	CRRA	Linear
20	(Cerroni, 2020)	Contextual decision	TCN	EUT	CRRA	-------
21	(Senapati, 2020)	A relative comparision of irrigated and rain-fed region (Odisha)India	HL	EUT	CRRA	Linear Model
22	(Zhao & Yue, 2020)	Special differences (USA)	TCN	PT	---------	Tversky and Kahneman Model
23	(Villacis et al., 2021)	Risk perception of Climate Chance among Latin American Farmers	TCN	PT	___________	Prelec

*Second-Order Model developed by Clibanoff Marinacci and Mukerji (2005)

**power risk aversion

Hansson & Lagerkvist (2012) tried to measure risk preferences among Swedish farmers using the Likert scale in a domain-specific framework. This study combined three factors of related objective decisions to analyze the farmers' risk preferences. First, the 'updated deliberate' factor comprises learning orientation, leading to the pursuit of new information about farming. Second, the 'carefulness and planning' factor comprises farm management strategies, resulting in financial management having a low debt-equity ratio, balanced crop rotation, and buying inputs at an appropriate time. Third, the 'progressive farming' factor involves using updated machinery, a storage facility for crop production, and entering into future contract markets for crop selling. Using a simple Spearman rank correlation method to observe the relationship between these factors, they found that the benefit of being up-to-date strongly correlates with a perceived risk factor. It implies that farm risk management is one of the strong determinants affecting a farm's business returns. Further, it concluded that farmers are risk averse in all domains, and risk preferences are primarily associated with their characteristics. Therefore, to make risk preference in the farm business, individual intrinsic factor is quintessential in affecting the risky decision.

In another study, Hellerstein, Higgins, & Horowitz (2013) used a lottery choice mechanism to measure farmers' risk preferences by providing a real monetary incentive to observe risk preferences. They try to observe the predictive power of risk preference measures in farming decisions. Observing individuals' elicited valuation of lottery using the open-ended approach of HL procedure became popular recently. This study suggests that lottery choices do not provide a reliable and adequate method to explain risk preferences in the case of farming decisions. Thus, willingness to take risks in farming decisions using the lottery choices must be framed in a context where risky behavior cannot be observed in isolation.

Lucas & Pabuayon (2011) analyzed rice farmers' risk perception and attitudes in rainfed lowland ecosystems in the Philippines. Using the Likert scale and HL procedure to evoke risk perception and risk attitude, they found homogeneity in risk perception in financial, production, and environmental domains associated with different cropping patterns. They found that most farmers are generally risk averse. Rainfed farmers in a homogeneous socioeconomic background had similar risk perceptions, but attitude risk varied with the situation. This study also found that socioeconomic factors do not significantly impact risk aversion across cropping patterns, although some economic factors, like wealth and credit factors, hold statistical significance. Such differences are attributed to subjective choice of crop selection and farm investment, which varies with risk perception in cropping patterns.

Menapace, Colson, & Raffaelli (2013) examined the relationship between an individual's risk attitude and their subjective beliefs regarding uncertain outcomes resulting from agricultural losses caused by adverse weather events. Experimental data in this study underlining the subjective expected utility theory of Savage (1954) found a strong relationship between subjective belief and risk attitude. More risk-averse farmers were more likely to perceive a greater probability of farms occurring losses. This study has a significant policy implication for understanding subjective belief and its impact on farm decisions.

Findlater, Satterfield, & Kandlikar (2019) analyzed farmers' decision-making and behavioral aspects while challenging the assumption of the economic rationality of optimization behavior. This study used the cognitive model to focus on South African farmers producing large-scale commercial grain. They analyzed how they assess and coordinate decisions about the weather, climate variability, relative climate change, agronomics, and economic, political, and personal risks in daily life. Their findings indicate that optimization is not the sole objective of decision-makers in a fixed time frame. Farmers behave in an asymmetrical world where duly coordinated risk management processes arise from various factors and compete and complement each other. Therefore, the objective varies on different scales and time frames. This study also found risk aversion behavior among farmers and their decisions having a different frame of reference with relevant endogenous and exogenous factors, i.e., the learning effect in the decisions. In understanding the cognitive responses of farmers to weather and climatic risk, this study further accounts for two important non-optimizing strategies for making practical decisions in uncertainty. First, it reports that due to cognitive and informational limitations and loose coordination in decision-making, farmers' objective is akin to satisfying behavior rather than optimizing utility. Second, there is skepticism about including new risk factors and information in response to changing the existing entity set; their diverse risk perception provides important differences among individual behavior. This theory has significant policy implications in understanding the farming decision in climatic change and instantaneous reaction to changing the condition of a policy initiative to support the farmers' adopting behavior.

Quinn, Huby, Kiwasila, & Lovett's (2003) study focused on the sources of potential risk perception for the local community in a semi-arid region of Tanzania. This study surveyed one of the most underdeveloped regions where the government tried to support and develop an agricultural system where people are primarily involved in pastoral and hunting-gathering activities. This study used the risk-mapping (Smith et al., 2000) technique to observe the significant risk factors of the local community. They found visible differences in risk perception among the local population and risk perception determined by the availability of natural resources and dependency on local livelihood. It found that risk perception varied with changes in livelihood, and agricultural farmers deferred in risk perception against hunters. Farmers' livelihood strategies, i.e., irrigation and the weather, became important determinants for sources of risk perception. This study also observed gender-based heterogeneity in risk perception.

Jin, He, Gong, Xu, & He (2017) also measured the farmers' risk attitude in rural China. This study used the Multiple Price List (MPL) experimental procedures and the risk assessment method from survey data to compare these two risk elicitation methodologies. They found that risk aversion behavior among farmers and individual risk preferences vary across elicitation methods. The study also found that exogenous factors, i.e., gender, age, and height, are economically significant, and men generally dare to take more risks than women. Observing the survey measure on general risk verifying the incentive-compatible field method of MPL, they found that response to the general risk question significantly impacted the subject decision. Appropriately designed survey technique measuring risk attitude provides useful individual risk elicitation behavior. Finally, they observed that only 48 percent of the total sample exhibited consistency in risk attitude in both methods. A similar study by Reynaud & Couture (2012) was conducted among French farmers trying to compare two elicitation methods- Holt & Laury's (2002) method and Eckel & Grossman's (2008) method, for analyzing stability in risk attitudes. This study focused on understanding the variation in risk attitude elicited by these methodologies using data from the same sample of subjects. One of the substantive findings of this study suggested that individual risk preferences vary significantly with respect to the elicitation method. While the outcome of the HL technique suggested that respondents are relatively less risk-averse, the Eckel & Grossman (2008) method found that risk preference ranking remains stable across tasks. Another result of the study also validated the notion of context-dependence risk preferences. Both psychometric questionnaires and experimental methods found that eliciting risk behavior measures often correlated with risk attitude towards investments and attitude towards hypothetical events. Various scholars have also tried to explain this instability in risk preferences theoretically.

Schaak et al. (2017) focused on a decision maker's risk attitude influencing uncertain agricultural outcomes. This study used HL and BDM (Becker et al., 1964) methods and a detailed questionnaire, specifically focused on the decision on farm diversification, understanding, and forecasting economic behavior in production decisions. Farm diversification is one of the tools farmers use to reduce risk factors. Theoretically, farm diversification decisions should be explained by individual risk attitude. Regression analysis found that experimental data on individual risk attitude does not significantly explain the farm diversification behavior. Therefore, this study concludes that experimental risk attitude measures cannot simply explain or be used to predict farmers' behavior regarding risky or uncertain decisions.

In order to examine agricultural risk and uncertainty characteristics, Ullah et al. (2016) differentiated broadly two significant sources of risk- business risk and financial risk. Business risk consists of production, market, institutional and personal risks. On the other hand, financial risk consists of various methods of financing agricultural production from the beginning to the last disposal of the crops. This study reveals that farmers' risk perceptions, attitudes, individual characteristics, and institutional factors, i.e., favorable economic, agricultural, and technological policies in developing countries, are essential in determining the adaptation of agricultural decisions under risks and uncertainty. In another study to examine the possible options for managing severe risks in agricultural production, he analyzed how various options are adopted in risk management as tools and applied by farmers as risk management strategies. (Ullah, et al, 2015; Ullah et al., 2016). There was evidence in favor of multiple risk management tools being simultaneously adopted by farmers.

Ahsan (2011) studied aquaculture farmers' risk perception and risk management strategies in Bangladesh's coastal region. The main objective was to describe risk perception and risk management response and to highlight the working conditions, motives, strategic decisions, and objectives of those farmers involved in this business. Though close to 18 percent of farmers reported a lack of an alternative business for livelihood as a reason for being in this business, around 70 percent of farmers reported this business, especially shrimp farming, as lucrative.

Around 50 percent of farmers were willing to scale up their businesses through productivity, and 35 percent wanted to scale up their businesses by expanding the farm area. Only 5 percent of farmers responded to scaling down their production and coming out of business shortly. These figures indicate that individuals have set various goals and objectives, and considerable variations exist.
Regarding risks perceived by farmers, shrimp disease, seed prices, intermediaries' negative intervention, and future prices of shrimps in the foreign market were reported to be the primary sources of risks. Accordingly, resolving these uncertainties was the most important risk management strategy. Socioeconomic characteristics, i.e., education, experiences, family size, age, and training, were significantly important in influencing risk perception and management strategies.

Flaten et al. (2005) examined risk perception and adopted risk management strategies among Norway's organic and conventional dairy farming methods. This study was conducted using a survey method and found that institutional and production risks are perceived as primary risk sources and that organic farmers are less risk-averse than conventional farmers. The differences in risk perception were found to be most pronounced for the cost of input factors and institutional policies about animal welfare. Various socio-economic factors also significantly influence risk response and risk management strategies. Farmers with agricultural training and education preferred organic farming. The most important risk management strategies among farmers were financial measures, insurance, and disease prevention, in general.

Pennings & Leuthold (2000) examined farmers' behavioral risk attitudes and relationship with future contracts. Future contracts are the most common risk management strategy in a well-developed market where information and individual decisions are considered more crucial. Heterogeneity among farmers is examined by taking into account indirectly observable variables. The study found a strong relationship between farmers' risk perception and psychological traits. Taking individual assessment errors into account is essential when understanding the farmers' behavior while entering the future market. This study also found that farmers' market orientation, entrepreneurial behavior, perceived risk reduction, market performance, and perceived risk exposure are essential factors influencing behavior while entering the future market. Farmers' risk attitudes were also significantly associated with participation in future contracts. However, some studies found that farmers' risk attitude behavior is inconsistent with the adoption of futures market participation in the agriculture market (Goodwin & Schroeder, 1994).

Moser & Musshoff's (2015) study was perhaps the first of its kind to examine the use of risk-increasing and risk-reducing production inputs in relation to the experimentally measured risk attitude among farmers. Using HL experimental procedure and Just & Pope's (1979) production function, this study analyzed whether high-risk-averse farmers choose more risk-reducing and less risk-increasing production inputs than their counterparts. Five production inputs were under investigation, viz., fertilizer, herbicides, labor, plot size, and plantation age. The results indicate that farmers considered fertilizer as a risk-decreasing input, while herbicides and plot size were treated as risk-increasing production inputs. The effects of labor and plantation age as input risks on output were ambiguous. Risk-averse farmers used more fertilizer and fewer herbicides as inputs in the process of choice selection. Such inputs may induce a reduction in output risk. This study found that farmer's risk attitude measured through the HL experimental procedure was consistent with actual decisions.

A recent study by Vollmer, Hermann, & Musshoff (2017), an extension to its previous work that employed HL experiment to analyze farmer's production risk, used Just and Pope's (1979) production function to analyze production behavior among German farmers. This study used panel data to explain farmers' risk attitudes to predict farm management behavior and found a significant negative relationship between the farmers' risk attitude and output variance that depicts production risk. Farmers with higher risk aversion decisions were found to have more stable production functions. Moreover, the HL procedure could explain farmer's risk attitude in production decisions. This outcome affirms that the validity of the HL procedure can predict the farming decision, contrary to the earlier studies (Hellerstein, Higgins, & Horowitz, 2013; Menapace, Colson, & Raffaelli, 2013).

de Brauw & Eozenou (2014), in another study of a developing country, Mozambique, analyzed the risk aversion behavior of sweet potato farmers by employing the constant relative risk aversion (CRRA) utility function. The lab-in-field experiment included a unique characteristic of a large subsample of husband and wife together in the process of choice selection. This study found that the rank-dependent utility model is more appropriate for explaining risk preferences. Further, farmers' risk behavior is consistent with the power risk aversion[12] utility model rather than Constant Relative Risk Aversion (CRRA).

In an attempt to measure risk attitudes from various risk responses (like financial, marketing, and production) in the agricultural production process, Bard & Barry (2000) developed an attitudinal scale from the responses of 86 farmers in Illinois. The study collected data in two parts; the first from personal interviews and the second from the experimental "close-in" method. They found that less risk-averse respondents and their self-perception about risky attitudes were unreliable in reflecting one's underlying attitude.

In the recent literature about public policy, economic forecasting, and understanding the complexity of human behavior and its effectiveness, behavioral economists have emphasized borrowing from the psychological literature, specifically tools and techniques from the discipline to apply to economics. Individual perception and attitude are central to understanding the origin of human thoughts and behavior. However, in terms of comprehending risk perception, individual attitude to specific sources of risk plays a key role (Sjoberg, 1980, 2004). Such attitude, in turn, significantly influences individual risk management strategy (Hardeker et al., 1997).

Individuals always search for generalizable rules and patterns from their insight and intuition through trial and error methods based on the best available knowledge. Sometimes, they reach the authentic path or procedure to improve engagement with risk and uncertainty through evolutionary approaches, which ultimately provide risk knowledge to resolve hidden facts (Slovic, Fischhoff, & Lichtenstein, 1982). These approaches influence choice behavior as choice architecture is influenced by the environment (Thaler & Sunstein 2009).

Different conceptual approaches define risk-taking as a need based on external factors (Bonss, 2013). Developed evolutionary behavior characterized by an individual's past experiences leads to a better understanding of risk patterns and nature (Greitemeyer, Kastenmuller, and Fischer, 2013). Various human brain activities (like heuristics, framing, anchoring, etc.) help them make better decisions in a risky environment (Gigerenzer et al., 2001). However, the human brain also has limitations in calculating risk prospects, as emphasized by Tversky & Kahneman (1974).

[12]Expo-Power utility function was proposed by Saha (1993) suggested that this utility function reduces the priori restriction and better captures decision-making under risky behavior.

It is well-known that intrinsic factors (like belief- individual perception about issues and objects related to him) are at the heart of individual behavior. To quantify such behavior into a range like maximum positive value to maximum negative, we have to assume that individuals hold the reciprocity of both sides' valuation of positive and negative numbers in the evaluation process. It means that individual cognition can quantify the observation by evaluating it. Quantifying a person's risk attitude is considered a latent variable that is not directly observable. However, it can be indirectly identified by developing the scale to measure risk attitude, considering the attitude as a cause of the behavior.

Hill (2009), in their study on Ugandan coffee farmers, analyzed risk aversion in production decisions. This study used the stated preferences and beliefs to identify risk aversion with nonparametric and regression analysis. It concluded that higher risk aversion leads to the lower allocation of resources in risky perennial crops and found lower labor allocation towards the risky crop of coffee. This effect held true irrespective of the income status of the farmers. This result also emphasized understanding the role of risk and risk preferences in observing various decisions about specific farmer-level outcomes, input, and crop selections.

2.6 Risk or Uncertainty among Indian Farmers

Several studies focus on characterizing risk preference among farmers. Generally, it is presumed that farmers are risk-averse. When measuring risk preference, it is often assumed to be a Constant Relative Risk Aversion (CRRA) utility function. However, this assumption raises several questions, and the consequences of this assumption without testing with actual observations are unclear. Another conceptual framework used in many studies is the EUT to explain risk preferences. Notably, behavioral economists argued against these frameworks and raised various concerns after Kahneman & Tversky (1979) proposed the idea of "Prospect Theory." Within the PT framework, individuals make decisions based on perceived gains and losses with probabilistic alternatives where risks are involved, and probabilities of different outcomes are unknown. This leads to the alternative utility framework for choice behavior under uncertainty (de Brauw & P. Eozenou, 2014; Liu, 2013; Tanaka et al., 2010; Harrison, 2010), and most of these works on risk preference analyzed with the help of experimental data.

Binswanger (1980, 1981) was perhaps the first to provide a formal study of analyzing the farmer's risk aversion behavior in developing countries. This study examines the behavior of Indian farmers in both hypothetical and real payoff lotteries within an experimental framework. The study was designed to have fixed probabilities for the outcomes, while the outcomes varied. Despite most individuals behaving as risk-averse, a substantive number of individuals preferred risk-neutral, neutral to negative, and indifferent when stakes were very low. As the stakes increased over time in the game, individuals became more cautious about risk-taking; 80 percent were intermediate or moderate in response to risk aversion. Overall, this study concluded that farmers' choices were consistent with increasing relative risk aversion (IRRA) and decreasing absolute risk aversion (DARA). A contemporary study by Dillon & Scandizzo (1978) in Brazil found similar risk aversion behavior among small and subsistence farmers. Using the hypothetical risky options among two alternatives of risk and subsistence with certainty, most farmers were risk averse.

Further, using similar methodology in their studies, Miyata (2003) and Wik et al. (2004) found comparable results in the studies of Indonesian and Zambian farmers, respectively. Mosley & Verschoor (2005) compared data from three countries (Ethiopia, India, and Uganda) and found no significant relationship between risk aversion behavior and individual characteristics such as age, literacy, gender, income, and wealth. They found a significant correlation between data collected through real payoff lottery choices and the response from hypothetical certainty equivalence. Contradicting these results was Yesuf & Bluffstone's (2009) study in northern Ethiopia, which found a significant relationship between risk aversion behavior and individual socioeconomic characteristics (such as income, wealth, and other household composition)

Maertens Chari & Just (2014) designed an experiment using real input (seed variety). This study was conducted in Southern India[13]. An estimate for average yield was obtained by asking farmers to design the crop yield distribution. The findings of this study indicated a high potency of risk-seeking behavior among farmers. Nearly half of the farmers responded as risk lovers; wealth and assets strongly influence risk-loving behavior. One of the interesting findings was that individuals were more assertive to pay for the crop seeds initially, but later, even after a decline in the variance,

[13] These villages have been selected for Village Level Study (VLS) program over 35 years by the International Crop Research Institute of the Semi-Arid Tropic (ICRISAT). The Binswanger (1980) study on observing risk attitude was also conducted in the same villages.

individual willingness to pay for seeds changed significantly with minimal pace. This might be the learning effect where an individual prefers later lotteries to earlier ones to the next game, which might underestimate the riskiness. Apart from that, an external and personal character might also be important impetuses to induce risk-seeking behaviors. In this study, the potential for investment in irrigation and children's college education reflected strongly to induce risk-seeking behavior.

Another study among Indian farmers by Raghunathan, Gaurav & Singh (2018) aimed to observe the risk behavior and potential reason for violating risk aversion. This empirical study was based on self-reported experiences of Gujarat paddy and cotton farmers. They analyzed the violations in the First Order Stochastic Dominance (FOSD) and Second Order Stochastic Dominance (SOSD). They found that nearly half of the farmers were violating the FOSD, while around 80 percent were violating SOSD. No clear pattern emerged in the analysis to explain the cause of violation among farmers; however, a reasonable inference was drawn that when farmers violated one condition, they were more likely to violate at least one more condition imposed by FOSD. Farmers' income risk, presented as yield risk or price risk, does not seem to influence the violation of any of the conditions imposed by the FOSD.

Interestingly, crop productivity is one of the reasons that lead farmers to violate the assumption. John M. Antle (1987) also studied risk attitude behavior in a village (Aurepalle). It was also among the six villages taken in Binswanger's study. An econometric analysis was employed to study the risk attitude of rice-producing farmers using similar technology. It found higher heterogeneity in the risk attitudes regarding relative risk behavior in the risk premium. This study concludes that differences in risk attitudes among individuals might be attributed to individual characteristics or preference variations over time. Psychologists and economists have often emphasized this interpersonal variation in economics in the literature.

2.7 Nonlinear Model and Utility Analysis in Agricultural Decision

Despite the expected utility theory being the dominant theory of decision-making under risk, numerous studies have raised concerns about using descriptive analysis (Harrison et al., 2010); Humphrey & Verschoor, 2004a; Humphrey & Verschoor, 2004b). They recommend that the nonlinear model is more appropriate to describe choice under risk and uncertainty. These studies focused on observing the competing models of expected utility theory against prospect theory

(Blavatskyy, 2013; Bocquého et al., 2014; Harrison et al., 2010) and concluded that no single model explained the risk and uncertainty behavior uniformly. Harrison et al. (2010) concluded in their study in developing countries (Ethiopia, India, and Uganda) that the expected utility model better explains only 50 percent of the respondents, and the remaining sample follows the subjective probability model of the behavior choice. Galarza (2009) also found that prospect theory better explains Peruvian farmers characterizing subjective distortion of the underlying probabilities in their risky decisions. It is fair to say, accordingly, that prospect theory is more appropriate for the subjective probability model in risky prospects.

Elicitation of risk preference among farmers is widely analyzed using the CRRA utility function and recent advances in experimental procedures. Binswanger's approach to measuring risk aversion in a low-income country (India) estimated the Arrow-Pratt coefficient. This model is criticized as the embedded expected utility model was arguably considered inappropriate (Pannell et al., 2000; Mosley & Verschoor, 2005), and the sole focus on the method of utility maximization in farm management is unrealistic. Moreover, Binswanger (1980) also suggested that farmers' risk attitudes cannot be fully explained by the expected utility alone, as there are differences in their constraint sets regarding inputs, credit, market access, etc.

Finally, to measure the nonlinear utility framework in the risk analysis, a PT model proposed three different parameters to evaluate the risky behavior of an individual – utility curvature, loss aversion, and probability weighting. Suppose a farmer is a utility maximizer. Consider the PT model. In that case, it argues that his behavior is more likely to be risk-averse in the gains domain and risk-seeking in the loss domain. Utility curvature reflects the nature of the utility curve, which generally varies between 0 and 1. If the coefficient of utility curvature leads to zero, it means a higher degree of concavity concerning changes in gains. In other words, the decision-maker is more sensitive while increasing the changes in gains. On the other hand, if the coefficient of utility curvature leads to 1, then the utility curve will be straight, and there will be less variability in the sensitivity for change in wealth.

Parameters such as loss-aversion and probability weighting are other important coefficients in the model. Loss aversion emphasizes that decision-makers respond more to losses than the equivalent gains. In the context of the agricultural decision, those farmers who are more loss-averse might use less pesticides and fertilizers because of higher sensitivity to health caution. Similarly, probability weighting is a distortion in the objective probability; it suggests that a large value in the probability has been underweighted while small probability values have been over-weighted during the decision-making. It helps understand the demand for insurance and contract policy; a low-probability default of risks and contract failure might be over-emphasized by the farmers.

Table: 2.3 *Estimated Parameters of Prospect Theory Model from Various Studies*

No.	Studies	Utility curvature	Loss aversion	Prob. weighting
1.	(Nguyen, 2011) Fish farmers Vietnam	1.012	3.225	0.96
2.	Tanaka et al., (2010) Rural popl. In Vietnam	0.59	2.63	0.74
3	Nguyen & Leung (2010) Livestock farmers in China	0.62	2.05	0.75
4.	Liu (2013) Cotton farmer China	0.48	3.47	0.69
5.	Bocquého et al., (2014) French farmer	0.28	2.28	0.66
6.	(Bougherara et al., 2017). French farmers	0.63	1.37	0.79 G & 0.84 L*
7.	Liebenehm & Waibel (2014) West African farmers	0.11	1.351	0.133
8.	Zhao & Yue, (2020) USA farmers	0.33	1.596	0.696

* Probability weighing is calculated separately for gains and losses

2.7.1 Estimation of Utility Curvature

Some studies used the Maximum Likelihood method to estimate the structural model of preference analysis (Bocquého et al., 2014; Bougherara et al., 2017) as an appropriate model for farm decision-making. These studies were conducted in France in two regions (Bourgogne and

Champagne-Ardenne). While Bocquého et al. (2014) estimated a utility curvature coefficient of around 0.28, Bougherara et al. (2017) estimated a comparatively higher utility curvature coefficient of 0.634 using a Prelec function. These differences in coefficient described through the sample characteristic elucidated that the farmers, on average, exhibited a high level of education (Bougherara et al., 2017). However, farmers' intrinsic characteristics of a pessimistic nature might vary in response to changes in wealth. A significant variation in estimated values is observed when comparing studies from developing economies using the Prelec function (see Table 2.3). Some studies found that the diminishing sensitivity of changes in the gains is potentially significant, as reflected in Table 2.3 of cotton farmers in China, Liu (2013), West African farmers in general, Liebenehm & Waibel (2014), and wheat farmers in France Bocquého et al., (2014).

2.7.2 Estimation of Loss Aversion

Table 3 presents the estimated coefficient in the prospect theory framework, where loss aversion has also been estimated with varied results in various studies. It measures the asymmetric curvature relative to the reference point where the loss-aversion parameter is greater than one while indicating loss seeking otherwise. A recent study by Zhao & Yue (2020) estimated risk behavior among USA farmers between two crops (commercial and perishable) producers with a similar theoretic model. This study estimated varied coefficients, i.e., utility curvature 0.327, loss aversion 1.596, and probability weighting 0.696. Although this study did not find any significant relation of loss aversion to explain the individual behavior of farmer characteristics, Liu & Huang (2013) highlighted a significant role in explaining pesticide use among Chinese cotton farmers. The estimated parameter of the demographic characteristic of producers' income was statistically significant in loss aversion. In contrast, particular belief about crop insurance is responsible for risk aversion and probability distortion.

Similarly, Bougherara et al. (2017) and Galarza (2009) also used Tversky & Kahneman's probability function in their respective studies, and the utility curvature parameter was estimated to be 0.614 and 0.74, respectively. In contrast, probability weighting parameters were 1.374 and 0.54, respectively. Further, other studies (Nguyen & Leung, 2010) and Tanaka et al. (2010) on a rural population in Vietnam found similar results (see. Table 2.3) in developing as well as developed countries, except for fish farmers in Vietnam (Nguyen & Leung, 2009),

2.7.3 Estimation of Probability Weighting

Probability weighting measures the marginal sensitivity to changes from a reference point. The data presented in Table 3 of probability weighting parameters found that Vietnamese fish farmers are less sensitive than Vietnamese rural farmers. The probability weighting among French farmers was estimated to be 0.66, close to the original parameter of Tversky & Kahneman (1992). However, in the study among French farmers, the probability weighting was estimated for gains and losses, respectively, and it found that probability distortion over the gains and losses was significant (Bougherara et al., 2017).

Liebenehm & Waibel (2014), a study among West African cattle farmers, suggested more risk-averse and low (0.133) probability weighting than for the farmers in developed countries and China. Compared with the risk exposure among farmers in other parts of the world, African farmers were prone to a higher risk of exposure to drought, floods, pests, and disease. In addition, these farmers worked in an environment with limited access to government support regarding institutional stability, market support, and insurance policies.

2.8 Discussion

In agricultural economics, understanding risk behavior through an experimental approach can be broadly divided into three methods. The first approach of contextualizing the experimental design uses input factors to make preferences based on their choices; we generally elicit risk responses among farmers. This method has been used in various contexts but cannot be generalized to the other factors causing the risk behavior. This model is criticized for its complexity and costs. Nevertheless, Harrison and List (2005) highlighted the importance of field and lab experiment[14] and it can be said that both these models are effective in specific contexts.

The second method of designing an experiment with a given probability and with respective monetary incentive procedures is simple enough to explain to the participants, as seen in Binswanger (1980). This method has been praised by Mosley & Verschoor (2005). The HL method has recently been widely used in economics for risk preferences. However, the critics of the experimental method in economics raised concerns about behavior in a laboratory setting

[14] Laboratory experiments offer controlled environments where potential confounding variables are kept constant across the studied groups. On the other hand, field experiments address this concern by transferring investigations from controlled lab settings to more authentic, real-world contexts.

experiment and actual behavior in real-world decision-making (Benz & Meier, 2008). Harrison et al. (2007) tried to observe the reliability of using individual behavior observed in a laboratory setting as an indicator of behavior in real-life, natural settings. Specifically, it focuses on the context of understanding risk attitudes and how the controls commonly employed in laboratory setups might influence subjects' behavior differently from how they would behave in real-life situations. It finds that individuals might demonstrate moderate risk aversion in laboratory setups or scenarios with minimal uncertainty, but they become more risk-averse when facing real-life situations involving background risk[15]. This aligns with the principles of conventional expected utility theory, which predicts that people are more averse to risk when faced with uncertainty in real-life situations. Another critique for the HL method was also made, suggesting that it is influenced by the order effect (Harrison & Rutström, (2008) and captures the behavior in a range of payoffs derived in the experimental setting (Drichoutis & Lusk, 2016). Next, a method evolved from HL procedure to capture the prospect theory parameters. It was developed by Tanaka, Camerer, & Nguyen (2010) and found the most frequent uses recently in various studies.

An individual's decision process following integration or segregation of the transactions can substantially impact his perception, whether they consider themselves better off or worse off after a series of transactions[16]. The previous transactions result in guiding principles for future decisions[17]. This is supported by Just & Peterson's (2010) study, which suggests that in decision-making under risk, a decision-maker is extremely sensitive to the impact of small changes in a continuous choice. This sensitivity causes inconsistency in the expected utility function. Therefore, it is tempting to imply that prospect theory captures such differences in the estimated parameters, i.e., utility curvature, loss-aversion, and probability weighting. It causes different socio-economic and contextual changes where farmers' behavioral responses report notable differences. Farmers face different types of risks and degrees of uncertainty in different geographical regions, which may cause differences in their intrinsic behavioral responses. Their risk exposure also varies with

[15] A background risk is defined as a risk associated with real-life events that cannot control as we can do in a laboratory setting.

[16] Thaler's (1999) theory of mental accounting that tries to explain mental process in ambiguous predictions suggests that sometimes individuals form groups to determine the perception of gains or losses.

[17] Richard Thaler (1999) proposed the theory of mental accounting complement the Prospect theory. It proposed that decision-makers perceive all previous outcomes and evaluate them to given cognitive capacity. He explains decision-maker psychology about accounting of gains and losses (hedonic editing) and the strategic behavior of achieving best possible option (also can be said maximization behavior) in the next decision outcome (hedonic framing).

the available information and resources. It was found that Chinese cotton and French farmers reported more loss-aversion behavior than Vietnamese farmers. It is also found that French farmers are more sensitive to changes in gains compared to the general farmers and livestock farmers in Vietnam.

On the contrary, African farmers reported high sensitivity behavior (Liebenehm & Waibel, 2014). This difference in farmers' responses to risk might be an intrinsic behavior in decision-making. With a wide variation in behavior under risk, policymakers must focus on individual responses and subjective notions of decision-makers to ensure a systematic analysis to assess the best options in the policy design.

Table 2.3 presents the estimated parameters from various studies using a similar experimental method HL and prospect theory. It indicates a range of results that characterized decision-makers' responses from extreme sensitivity behavior of loss-aversion and risk-aversion and probability weighting to insensitivity in the risky behavior. It found that farmers in the developed world are generally more sensitive than farmers in the developing world. It is because they are better equipped and well-informed about their decision.

The model of the nonlinear approach has been appreciated; it observed that the measurement of risks and their responses are more efficient and precise in a nonlinear system (Hardaker et al., 2004). Hardaker et al. (2004) said that farmers' decisions on input selection, market and weather prediction parameters, and mean values are usually over-estimated or under-estimated, reflecting the subjective nature of biased behavior. These differences in mean values explain a downside risk that is always available irrespective of decision-makers risk-taking capacity. Nevertheless, the size of biases varies with the riskiness of a particular decision, context, and degree of risk aversion, all of which can be captured through this method, which makes it a useful model for better policy analyses and designs.

The critics of these experimental approaches in a lottery choice task say that adopting various contexts allowed for studying risk attitudes. However, studies reflect that the same individual risk preference varies over different experimental methods (Lönnqvist et al., 2015; Maart-Noelck & Musshoff, 2014) and are less stable (Isaac & James, 2000). Menapace et al. (2016) raised the question that lottery choice tasks are lacking in terms of resembling and contextualizing in the context of agricultural decision problems.

Another challenge raised in the experimental studies is that in high-stakes decisions, i.e., crop insurance and input use, decisions are generally measured through a proxy of a small amount of reward in the experiment. This budget constraint is usually applied to the research, allowing only a small fraction of the payout to be randomly assigned to the participants (Maart-Noelck & Musshoff, 2014). Many scholars have raised this concern that at the lower stake, decision-makers may be misspecified in terms of not revealing the actual risk behavior of farmers in real-world decision-making (Menaspace et al., 2016; Rabin, 2016; Vollmer et al., 2017).

Finally, compared with the previous studies using secondary data, the experimental method estimates a broader range of risk preference parameters. However, in measuring risk attitudes, it is challenging to capture the perception and preferences by this method directly. Studies estimating risk preferences from secondary data exhibit a range of risk behaviors from high-risk averse to risk-loving. An appropriate design of the lottery choice task provides sufficient scope to capture more accurate risk-taking behavior predictions.

2.9 Conclusion

This review highlights major studies about farmers' risk-taking behavior using the experimental approach. Agricultural economists use a wide range of methods to capture farmers' risk preferences. Our focus is on studies with an incentivized monetary reward experimental approach designed. We found earlier reviews focusing specifically on analyzing the methods (Charness et al. 2013) and region-specific (Iyer et al. 2020) and highlighted significant variability. The arguments in favor of variability are, first, methodological differences- measurement of risk preference may change when we use different methods to capture the risk of the same individual. Second, the measurement of risk preference may also vary over time. Finger et al. (2023) analyzed the instability of risk preferences among farmers and found that they change over time and methods.

This review highlighted the key features in agricultural decision-making, including capturing the heterogeneity of individual differences and context-specific risk preferences in which farmers in developed and developing countries exhibit substantive differences. Summarizing these studies to highlight the behavioral notion is always pointed out in various articles, but the HL approach became the suitable experimental method to capture it. It found a strong inclination toward this approach in numerous studies of various kinds to capture the risk preference.

Experimental method in economics is not a new phenomenon. It has around forty years of history and has been part of the critical methodological debate. This method provides substantial control over the context under which data are created, focusing on variables pertinent to a problem's study. The experimental approach can broadly be divided into two methods. The first method provides the decision-maker with complete information about different risk yields of real input variables, for example, seeds or other inputs, before asking about their choices in the given circumstances. The second experimental method considers that decision-maker risky behavior can be captured through a systematic risky game, which must be precisely elaborated to participants before the experiment is conducted. This is a new approach to studying risky behavior in agricultural decisions, in which the HL method has become one of the popular tools to analyze the various risky phenomena. This method provides a broader systematic set of choices that can capture the subjective behavior of an individual in decision-making.

Historically, the expected utility theory has dominated the theory of choice under risk and uncertainty. Under this model, it is generally accepted that probabilities are objectively given, and human behavior can be precisely explained through this model (Starmer, 2000). In this review, we have focused on alternative theory (CPT) derived from the individual prospect through evaluating the decision process. It is one of the prominent theory in decision-making. This model offers simple risk prospects by editing mechanisms to reduce complexity. It is also worth mentioning that these experimental methods complement each other to make a precise understanding of risk behavior.

Now on the theoretical front, Quiggin's (1982) model of Rank-dependent utility theory describes the outcomes ranked according to their desirability and corresponding cumulative probabilities, which transform into a weighting function. Tversky & Kahneman (1992) extended this model into cumulative prospect theory, proposed differentiated gains and losses, and ranked it according to probabilities. While evaluating risky prospects, decision-makers differentiate the outcomes weighting from biased behavior. Kahneman and Tversky mentioned in their prospect theory that the value function consists of reference dependence in gains and loss domains, respectively[18]. The individual's choice in this model of risky prospects is framed in terms of gains and losses and subjective capability to evaluate the prospect, which incorporates the S-shape value function and inverse S-shape weighting function (Tversky & Kahneman, 1992).

While developing this alternative decision-making theory under risk and uncertainty, scientists have also applied it in several disciplines. In agricultural economics, several studies have applied this alternative model to explain the observed phenomenon of risk behavior. Collins et al. (1991) investigated changes in risk preference using survey data and found it consistent with prospect theory to a greater extent than with expected utility theory. They also estimated the risk aversion parameter from individually fitted utility functions and the coefficient of marginal risk response. The application of prospect theory in agricultural economics has grown in the last decade to comprehend the farmers' risk behavior and policy responses.

Finally, capturing the subjective risk behavior in response to the high and low probability events, it found that farmers frequently distorted such probabilities in the production decision (Duden et al. 2023). Farmers generally tailor their decisions based on heuristics and intuition in the decision-making. Such behavioral traits in economics and psychology have demonstrated a conscious application in decision-making under risk. It got considerable attention in the literature for analyzing farmers' responses to risk in agricultural decision-making, and the CPT model is a suitable model to explain such phenomena.

[18] The value function emphasizes making investment decision under risk is not related to the final outcome of investment but it is a function of assets position and magnitude of changes from asset position. Asset position derives from incorporating prospect of asset investment in future (see. Kahneman and Tversky, 1979).

Chapter 3

Farmers' Risk Behavior: Expected Utility and Prospect Theory Approaches

3.1 Introduction

Agricultural occupation involves inherently risky activities. Due to resource constraints and due to difficulties in accurate prediction of prices, output, and market availability, agricultural production entails a high exposure to risk. In such situations, poor farmers become more vulnerable due to limited options for mitigating risk and uncertainty. This often leads to difficulties in risk management and may result in making suboptimal agricultural decisions.

Risk preferences, sometimes called risk attitudes, represent an individual's response in terms of risk-taking. Depending on resource constraints and available information, farmers exhibit diverse risk attitudes, ranging from extreme risk aversion to risk-seeking behavior. Risk attitude is generally assumed to influence farmers' risk behavior in real-life decisions (Pennings & Garcia, 2001; Weber & Milliman, 1997; Willock et al., 2009). It is commonly assumed that farmers tend to be naturally risk-averse (Hardaker et al., 2004). Individual risk attitudes are crucial in decision-making, especially in farm risk management, as risk arises from information gaps and decision complexity (Hardaker et al., 2004). However, various studies have also found instances where farmers are willing to take more risks, exhibiting risk-seeking behavior (Maertens, Chari, and Just, 2014). Observing various risk behaviors in different domains and exposures is valuable when investigating farmers' responses to agricultural risks.

Farmers make decisions in different condition, such as high-risk agro-climatic regions as well as in relatively controlled, less risky environments (e.g., livestock farming). Additionally, governments often introduce various risk-mitigating policies to reduce risks in agriculture. For example, the Federal Crop Insurance Program offers a comprehensive plan for US farmers to mitigate market and production risks. Similarly, the National Agriculture Insurance Scheme (NAIS) and Minimum Support Price (MSP) serve as risk-mitigation tools for Indian farmers to reduce risks in agricultural production. The effectiveness of such schemes depends on how farmers respond to these policies, which varies based on their risk perception and attitudes toward various risk factors. Farmers' risk perception and attitude are crucial components that collectively influence individual risk behavior (Sitkin & Pablo, 1992).

For effective policy design, policymakers strive to comprehend a farmer's decision-making process concerning potential risk management strategies. Agricultural decision-makers frequently base their choices on personal circumstances and their ability to handle risk and uncertainty. Policymakers may sometimes struggle to grasp farmers' varying capabilities and differences in risk taking behavior. This may cause delays in policy design which is important for policy effectiveness. Given the significance of risk management, it becomes crucial to understand farmer risk behavior to develop improved risk management strategies and for policy designs. Farmers' responses to policy changes in potential risk management strategies are need to be grasped by the policymakers for better understanding of policy effectiveness.

In the ongoing theoretical debate, the expected utility theory has been predominant in studying farmers' risk behavior (Hardaker & Lein, 2010). It is typically assumed that risk preferences follow a constant relative risk aversion (CRRA) utility function (Delavande et al., 2011; Senapati, 2020). It is also assumed that decision-makers are well aware of their constraints and goals, acting as rational agents who optimize their self-interest[19]. However, there is increasing awareness and evidence in the agricultural economic literature that the expected utility model has limitations in its scope (Shaw & Woodward, 2008; Rottenstreich & Kivetz, 2006), especially in the context of complex decision-making with multiple goals for farmers. The expected utility theory provides a normative approach to decision analysis, including some unrealistic assumptions and prescribing how a rational agent should behave (Starmer, 2000). This may be valid in simple situations with

[19] Allais (1953), in his seminal study, empirically proved that individuals do not necessarily behave according to the expected utility maximization behavior. Later, psychologists and economists also supported this view provided various evidence in deviation of expected utility. Such experimental evidence against the EU model accumulated and evolved in the form of a behavioral theory proposed to explain it and prevail as an alternative model.

clear objectives. Agricultural production involves complex decision processes, and the expected utility theory appears to have difficulties to incorporate the subjective notions of decision-makers.

Prospect theory model is capable of capturing the subjective aspects of decision-making. Tversky & Kahneman (1979) examined significant behavioral characteristics and discovered systematic deviations in actual behavior from the behavior consistent with standard expected utility model. Although decision-making under risk is a complex phenomenon in the real world, people generally tend to use heuristics, rules of thumb, or biases, leading to these systematic deviations. Tversky & Kahneman (2012) interpreted these deviations as cognitive limitations and biases in risk and uncertainty scenarios.

Personal characteristics and perceptions of policy measures also influence a farmer's risk behavior. A farmer's response to risk as a mitigation strategy is based on their ability to cope with risks. For instance, if a farmer has adequate capital to secure their future against risk, better equipment, and sufficient information to assess the prospects of a decision, they might be more willing to take risks (Senapati, 2020). Binswanger (1980) also concluded that farmers' risk attitudes vary depending on whether the stakes in potential losses are high or low. He further noted that farmers' risk behavior is consistent with increasing relative risk aversion (IRRA) and decreasing absolute risk aversion (DARA).

Numerous studies are available that examine the determinants of risk behavior through experimental methods. Extensive use of HL and modified HL procedures in analyzing risk behavior is observed. The present study employs HL experimental methods to investigate the determinants of farmers’ risk behavior determinants through expected utility and prospect theory to understand models explaining risky behavior.

The primary contribution of this study to the literature lies in analyzing the determinants of farm and farmers' characteristics in risky decision-making. This study analyzes behavior through the HL procedure, a flexible method that captures farmers' behavioral characteristics (de Brauw & Eozenou, 2014). Also included are broader behavioral characteristics, such as experiences and family participation in decision-making. Additionally, we have incorporated broader wealth and asset indicators, including household and agricultural income, education expenditure, formal and informal debt, and landholding characteristics related to leasing-in and -out behavior. We have also included the number of rooms in the home as a wealth indicator. These wealth indicators are essential because they have varying levels of substitutability in terms of liquidation.

On a methodological level, this study has included power risk aversion utility functions in both expected utility and prospect theory and has compared the association between farm and farmers' characteristics. We have not found other studies that used models that capture broader assets and wealth indicators in this context. This experiment was conducted with the heads of households to elicit risk preferences and subjective probabilities using real payoffs. The general finding of this study is that probability distortion is a common phenomenon in risky decision-making, and various wealth indicators, as well as farmers' characteristics, were significant in determining risk parameters.

The chapter is structured as follows: The section 3.2 provides the literature review. Section 3.3 describes the experimental procedures for measuring risk aversion behavior. Section 3.4 outlines the utility models of decision-making. The results are presented and discussed in section 3.5. The final section offers and concluding remarks.

3.2 Measurement of Risk Preference and Previous Studies

The existing literature on farmers' attitudes towards eliciting risk is broadly categorized into three categories: studies that observe risk attitudes by estimating actual cropping decisions, including input usage and output data from the field (Antle, 1987; Chavas & Holt, 1996; Moscardi & de Janvry, 1977), using econometric models to estimate risk parameters based on household or firm survey data. Second, a method that captures risk behavior using self-assessed attitudes towards farmers' risk (Likert scale) (van Winsen et al., 2016; Bard & Barry, 2000). Finally, experimental techniques based on farmers' choices given risky lottery choices offered to them in order to estimate their attitude towards risk (Binswanger, 1980; Maertens, Chari, and Just, 2014; de Brauw & Eozenou, 2014).

The experimental method can also be divided into two categories: the first approach consists of systematic payoffs and respective probabilities as designed by Becker-DeGroot-Marschak (1964), Binswanger (1980), and more recently, Holt and Laury (2002). The second approach is more contextualized and frequently uses to apply agricultural inputs, such as the experiment with fertilized seeds and other input variables. These latter studies focus on specific contexts by analyzing decision-maker risk attitudes toward particular inputs (Maertens et al., 2014; D. et al., 2009; Lybbert et al., 2006). Most experimental studies have yielded mixed results regarding risk aversion behavior.

The literature analyzes risk behavior through experimental methods in rural India (Binswanger, 1980, 1981; Humphrey & Verschoor, 2004; Senapati, 2020). These studies highlight the importance of an alternative method (Binswanger, 1980, 1981; Humphrey & Verschoor, 2004; de Brauw & Eozenou, 2014; Tanaka et al., 2010; Nguyen, Q. 2011). Ihli et al. (2018) and Senapati (2020) used a similar experimental method and estimated the Constant Relative Risk Aversion (CRRA) parameter. However, more recently, de Brauw & Eozenou (2014) empirically tested the CRRA and power risk aversion (PRA) utility function and found that PRA is a better model to explain farmers' risk behavior. The present study also utilizes the power risk aversion utility function in the model. Similarly, in another study, Bocquého et al. (2014) in their study on French farmers concluded that the Cumulative Prospect Theory (CPT) is a better model compared to the Expected Utility (EU) model.

Both of these studies found that farmers are primarily risk-averse. On the other hand, other empirical studies have yielded mixed results. Some studies even have concluded that farmers are risk-seeking (D. et al., 2009; Maertens et al., 2014; Ross et al., 2012). These studies have presented contrasting views and have substantiated that the consensus on risk aversion behavior in the agricultural economic literature is insufficient to describe the complete picture of risky behavior and its determinants among farmers.

According to expected utility theory, various methods to determine risk attitudes are based on identical weights for every yield outcome. However, empirical evidence suggests that results differ between different experimental methods (MacCrimmon & Wehrung, 1986). For empirically investigating the likelihood of risky outcomes, researchers do not apply standard mathematical formulae of the symmetric rule to estimate probabilities but rather apply various behavioral phenomena. Tversky & Kahneman (1974) reported that various mental shortcuts, known as heuristics, are applied in decisions. Lichtenstein & Slovic (1971) also reported systematic differences between lottery choices and bids in gambling decisions.

When analyzing the determinants of risk behavior among farmers through lottery experiments, Binswanger's (1980, 1981) study on Indian farmers highlighted that farmers were moderately risk-averse. However, the degree of risk aversion increased with higher monetary stakes in the payoffs. He also concluded that farmers' risk aversion behavior was not associated with farm and farmers' characteristics such as age, gender, literacy, income, and wealth. However, more recently, Yesuf & Bluffstone (2009) conducted an experimental study on Ethiopian farmers and concluded that farm and farmers' characteristics were significantly associated with their risk aversion behavior.

Numerous studies have raised concerns about using EUT model in risky decisions (Harrison et al., 2010; Humphrey & Verschoor, 2004a; Humphrey & Verschoor, 2004b). They recommend that nonlinear models are more appropriate to describe choices under risk and uncertainty. These studies have focused on observing the competing models of expected utility theory against prospect theory (Blavatskyy, 2013; Bocquého et al., 2014; Harrison et al., 2010) and have concluded that no single model could uniformly explain risk and uncertainty behavior.

Farmers' risk and uncertainty production decisions rely heavily on a reference point. Such behaviors are explained by applying prospect theory, where the best outcome experience is considered a reference point (Tonsor, 2018). Prospect theory model describes that farmers exhibit risk-averse behavior for gain but risk-seeking behavior for losses. A famous example is the voluntary crop insurance program in the USA, where farmers' responses to buying insurance were very low. It was found that only 25 percent of eligible farmers accepted the scheme even after the government offered a 30 percent subsidy under the Federal Crop Insurance Act of 1980 (Glauber et al., 2002). Similarly, a study on farmers' response to the adoption of a new variety of potato seeds (an improved variety containing more nutrition) with less production variability and production with higher variability of the standard variety was hypothetically offered to the farmers (de Brauw & Eozenou, 2014).

The present study uses a subjective notion of decision-making behavior. It found more flexibility in explaining risk aversion preferences, and the rank-dependent utility model better explained the predictability of risk preferences. Numerous other studies (Tanaka et al., 2010; Nguyen, 2011; Nguyen et al., 2009; Maart-Noelck et al., 2013; Liu et al., 2012; Zhao et al., 2020) have also analyzed risk behavior through experimental methods and concluded that Cumulative Prospect Theory is better at explaining farmers' risk behavior.

3.3 Measurement of risk-aversion and Experimental Design

The present study employs HL experimental procedures. This procedure systematically exposes respondents to varying levels of risk. It is a relatively simple lottery game commonly used to measure risk aversion behavior. In this experiment, lotteries are systematically designed with increasing and decreasing orders in multiple price lists, where the differences between probabilities are 0.1. This experimental design ensures that each row represents a different level of risk with corresponding payoffs in consecutive order. The experimental procedure is presented in Table 3.1.

To describe the lottery game; in the first row, it is designed that if a subject chooses lottery A, they have a 10 percent chance of receiving rupees 180 and a 90 percent chance of receiving rupees 140. Similarly, an individual who prefers lottery B can receive rupees 350 or 10 payoffs with these, probabilities, respectively. This reflects the chances of obtaining a higher prize with higher risks. In row 2, the subject can win rupees 180 with a 20 percent probability and rupees 140 with an 80 percent probability in lottery A and rupees 350 and rupees 10 with probabilities 20 and 80 percent, respectively. Payoffs are held constant across the game in this experimental design. The probabilities for a given row are similar for games A and B but vary in each row. As a result, the expected value of the lottery for each row differs between the two lotteries. The expected value of lotteries increases for both A and B, but the expected value of lottery B increases faster than that of lottery A. Consequently, in row 1, expected value of lottery A is much higher than that of lottery B, but in row 5, the expected value of Lottery B exceeds that of Lottery A. Therefore, a risk-neutral individual would switch from lottery A to lottery B in row five. The switching point from lottery A to lottery B measures an individual's risk behavior. If the subject switches from lottery A to lottery B before row 5, they are considered risk lovers; if they switch after row 5, the subject is risk-averse. The degree of risk aversion behavior is captured by noting the switching row. If the subject switches in the last row, it suggests he/she is highly risk-averse. Similarly, if they prefer to switch from lottery A to lottery B in the first row, it suggests high risk-loving behavior. In this game, individual can choose lottery A or B and have a single chance to switch between choice of lottery A or B.

To capture risk, we assume that farmers are rational agents striving to maximize utility. Farmers were allowed to switch only once from lottery A to lottery B. Once they switch to lottery B, they are not allowed to switch back to lottery A. This simplifies the calculation process. However, it is worth noting that some studies allow multiple switching options to account for the noise in risky decisions (Andersen et al., 2006; Bruber et al., 2008; Galarza, 2009).

Table: 3.1 *Holt Laury Experimental Procedure*

	Lottery A				Lottery B			
No.	**ProbA1**	**PrizeA1**	**ProbA2**	**PrizeA2**	**ProbA1**	**PrizeB1**	**ProbB2**	**PrizeB2**
1	0.1	180	0.9	140	0.1	350	0.9	10
2	0.2	180	0.8	140	0.2	350	0.8	10
3	0.3	180	0.7	140	0.3	350	0.7	10
4	0.4	180	0.6	140	0.4	350	0.6	10
5	0.5	180	0.5	140	0.5	350	0.5	10
6	0.6	180	0.4	140	0.6	350	0.4	10
7	0.7	180	0.3	140	0.7	350	0.3	10
8	0.8	180	0.2	140	0.8	350	0.2	10
9	0.9	180	0.1	140	0.9	350	0.1	10
10	1	180	0	140	1	350	0	10

The experiment was administered by the researcher with the assistance of local support. Detailed experimental procedures are given in Appendix A. Initially, we engaged with the local community, seeking their cooperation and explained the purpose of our research work. We requested their consent to participate in both the experiment and the survey. Subsequently, we scheduled appointments with willing participants for the experiment. Each experiment and survey session was conducted individually with the respective resident respondents. During these sessions, we explained the experimental procedure clearly and encouraged participants to seek clarification. We also conducted a live demonstration of the experiment to enhance their understanding. Once the participants were confident and understood the procedure, we proceeded with the experiment and the survey.

In the experimental procedure, respondents were initially asked to choose between Lottery A and Lottery B for each row. After making their choices, they were required to randomly choose one card from a set of ten cards numbered 1 to 10. The particular card determines the row that would be used for the final payment game. Participants then played the game corresponding to the row they had previously preferred. This game arranged the number of red and black balls according to the row's specifications. For example, if a participant randomly selected row 7 and preferred game A of row 7, then in the final game, they played with seven black balls and three red balls for the final payment. In this context, black represented a 180 rupee payoff, while red represented a 140 rupee payoff. Conversely, if respondents preferred lottery B, black represented a 350 rupee payoff, and red represented a 10 rupee payoff.

Participants were also informed about the remuneration, which constituted a certain percentage of their winnings (20 percent) and was indicated in an envelope. The exact percentage was revealed to them after the conclusion of the game. This experiment was conducted in conjunction with another experiment. The percentage was disclosed upon completion of the game. The experimental game was presented as follows: We initially provided comprehensive instructions as outlined in Appendix A. We also conducted live demonstrations of the experimental procedures for enhanced clarity. Additional clarification was offered when necessary, and the game was played only with the participant's consent. After the game's conclusion, we collected additional information regarding the farms and characteristics of each respondent.

3.4 Model of Risky Behavior

3.4.1 Expected Utility Theory Model

For modeling decision-making under risk, the expected utility theory is defined as agents' utility maximization behavior. An agent prefers to choose between risky prospects by comparing the expected value of lottery options A and B. In this lottery experiment, let payoff be y_i^{jk} for individual i, in outcome j =1, 2 of the lottery k =A, B. The utility of this outcome is modelled as power function:

$$U(y_i^{jk}) = (y_i^{jk})^r \tag{3.1}$$

Now, this lottery must be designed in the gains domain only i.e., $y_i^{jk} > 0$ for all values of *i, j, k*. Therefore, the loss domain is unavailable in the equation. This is Tversky & Kahneman's (1992) utility model, where y_i^{jk} is payoff, and $r>0$ is the risk aversion parameter for the gain domain ($y_i^{jk} > 0$). Now, in a given utility specification, it implies that the individual exhibits either risk-seeking (convexity) for $r > 1$, risk-neutral (linear) for $r = 1$, and risk-averse (concavity) for $r < 1$ behavior. Next, in the experiment, subjects are asked to choose the lottery choices between lottery A and B, in which each lottery consist of payoffs y_i^{1A} and y_i^{2A} for lottery A with respective probabilities p_A and $1\text{-}p_A$. Similarly, for lottery B, payoffs are, respectively, y_i^{1B} and y_i^{2B} with respective probabilities p_B and $1\text{-}p_B$. Now, at each equation, the expected utility of subject *i* for each lottery can be written as the following:

$$\begin{aligned} EU_i^A\,(y) &= p_A * (y_i^{1A})^r + (1\text{-}\,p_A) * (y_i^{2A})^r \\ EU_i^B\,(y) &= p_B * (y_i^{1A})^r + (1\text{-}\,p_B) * (y_i^{2B})^r \end{aligned} \tag{3.2}$$

Therefore, assuming that subjects follow utility maximization behavior, observed choices are driven by a latent choice index Δ, derived from the difference between expected utility for lotteries A and B under the given expected utility model.

$$\Delta_i^{EU} = EU_i^A - EU_i^B \tag{3.3}$$

Considering Manski & Lerman's (1977) random utility model to derive an empirical choice model, utility is divided into two parts - the deterministic part containing the preference parameter to be estimated r_i and the random part capturing the unobserved heterogeneity ε_i. Suppose that preference parameters depend on the observable farmers' and farm characteristics (vector *Xi*) through a linear relationship. Choices can be specified as δ_i^* for each individual, and this can be written as:

$$\delta_i^* = \theta_0 + \theta X_i\,; \qquad \forall_i, \tag{3.4}$$

where θ_0 and vector θ are the estimated coefficients given the binary choice of lottery A and B. The following latent regression model can describe this

$$\delta_i^* = \Delta_i^{EU}(X_i) + \varepsilon_i , \qquad \text{and} \qquad \delta_i = \begin{cases} A \text{ if } \delta_i^* > 0 \\ B \text{ otherwise} \end{cases} \tag{3.5}$$

Where ε_i is the distributed error term with mean zero and variance 1. Further, to derive the probability that subject *i* will choose lottery A from the above equation;

$$\begin{aligned} Pr\,(\text{choose lottery A}|\ Xi) &= Pr\,(\Delta_i^{EU} + \varepsilon_i > 0|\ Xi) \\ &= 1 - Pr\,(\varepsilon_i \leq -\Delta_i^{EU}\ |X_i) \\ &= 1 - \phi\,(-\Delta_i^{EU}\ (Xi)) \\ &= \phi\,(\Delta_i^{EU}\ (Xi)), \end{aligned} \tag{3.6}$$

where, $\phi\,(.)$ denotes the cumulative distribution function of the normal distribution function. It lies in the interval [0, 1] for any value Δ_i^{EU}. Given this risk preference parameter, r_i will be estimated with maximum likelihood estimation procedure. Further, the likelihood of observed choices based on the expected utility and power utility specification, defined as being true, is as follows,

$$\ln L^{EU}(\delta, X; r) = \Sigma\,[\ln \phi\,(\Delta_k^{EU})\ X\ I\,(\delta_k = A) + \ln\,[1- \phi\,(\Delta_k^{EU}\,]\ X\ I\,(\delta_k = B)] \tag{3.7}$$

where, *k* is the index of lottery choices pooled of subjects, *I* is the indicator function, and δ_k denotes the choice of lottery A or B. Finally, the maximum-likelihood estimation for the risk parameter is, therefore:

$$r^\wedge = \arg\max \ln L^{EU}(\delta, X; r) \tag{3.8}$$

3.4.2 Cumulative Prospect Theory Model

Cumulative Prospect utility model proposed by Tversky & Kahneman (1992) included psychological features in the utility model. Unlike the farmers' risk behavior determinants, the sole factor reflects the risk behavior. They justified that loss and gain behavior have different characteristics- in a loss scenario, decision-makers are more sensitive than the gain domain.

Similarly, given probabilities in the lotteries are also distorted during the evaluating process. This is caused by the notion that assessment of lotteries is weighted subjectively. Tversky & Kahneman (1992) renamed the utility curvature as a "value function," which is derived over the gains and losses from the lotteries rather than "terminal wealth," as the expected utility model proposes. In a given utility model of a risky game, let payoff be y_i^{jk} for individual i in outcome $j =1, 2$ of the lottery $k =A, B$. The utility of this outcome is:

$$U(y_i^{jk}) = (y_i^{jk})^{\alpha} \tag{3.9}$$

It is important to note that this lottery is designed to gain domain only ($y > 0$); therefore, the loss domains parameter is unavailable in the equation. This is Tversky & Kahneman (1992) utility model where y_i is the lottery payoff of individual i, and $\alpha>0$ is the risk aversion parameter (value function) for the gains domain ($y_i^{jk} > 0$). Now, in a given utility specification, it implies that the individual is either risk-seeking (convexity) for $\alpha > 1$, risk-neutral (linear) for ($\alpha = 0$), or risk-averse (concavity) for $\alpha < 1$.

Next, in the given experiment, subjects are asked to choose between lottery A and B, in which each lottery consist of respective payoffs y_i^{1A} and y_i^{2A} for lottery A with respective probabilities p_A and $1\text{-}p_A$. Similarly, for lottery B, payoffs are y_i^{1B} and y_i^{2B} with respective probabilities p_B and $1\text{-}p_B$. Now, the following Tversky & Kahneman (1992) decision model of weights in the cumulative probabilities for a subject i for each lottery can be written as:

$$\text{CPT} = \begin{cases} w(p_A) * u(y_i^{1A}) + (1 - w(p_A)) * u(y_i^{2A}) & if\ y_i^{1A} \geq y_i^{2A} \geq 0 \\ & or \quad y_i^{1A} \leq y_i^{2A} \leq 0 \\ w(p_A) * w(y_i^{1A}) + w\,(1 - (p_A) * u(y_i^{2A}) & if\ y_i^{1A} < 0 < y_i^{2A} \end{cases} \tag{3.10}$$

Where $w(.)$ is a probability weighting function that is strictly greater than 1, it reflects the subjective distortion of given probabilities that several studies have justified (Gonzalez & Wu, 1999; Babcock, 2015 & Gonzalez-Ramirez et al., 2018). Various studies have referred to these probability model[20] (Gonzalez & Wu, 1999; Babcock, 2015 & Gonzalez-Ramirez et al., 2018). We used Prelec (1998) probability weighting, $w(.)$ function is defined as:

$$w(p) = exp\ [-(-\ log\ p\ \ )^{\gamma}\ ] \qquad (3.11)$$

where γ is the parameter controlling the curvature of the probability weighting function ($\gamma > 0$). This parameter can be interpreted as an index of likelihood sensitivity, with $\gamma = 1$ reflecting the absence of probability distortion ($w\ (p) = p$). In other words, as γ tends to 1, the distinction between different probability levels gets more blurred, and probabilities tend to be perceived as all equal. This assumption, backed by substantial empirical evidence, gives the weighting function an 'inverse S-shape'. In the case of a binary prospect such as a lottery, it characterizes the overweighting of the low-probability outcome and an underweighting of the high-probability outcome. If $\gamma > 1$, the function takes the less conventional 'S-shape.' At the extreme, if γ is very high, probabilities tend to be perceived as either 0 or 1. In CPT, risk behavior results from the interplay of utility curvature, loss aversion, and probability weighting. The CPT model reduces to the EU-power model if probability weighting and loss aversion are equal to 1.

Assuming that subjects follow a utility maximization behavior, observed choices are driven by a latent choice index Δ derived from the difference between utilities for lotteries A and B under the given expected utility model. This model also included an individual error in decision-making.

$$\Delta i^{CPT}\ =\ CPT_i^A\ -\ CPT_i^B \qquad (3.12)$$

A derivation of the likelihood function for CPT follows similar procedures as earlier described for the expected utility model.

Considering Manski & Lerman's (1977) random utility model to derive an empirical choice model, utility is divided into two parts- the deterministic part contains preference parameter to be estimated ri, and the random part captures heterogeneity ε_i. Suppose that preference parameters depend on observable farmers and farm characteristics (vector Xi) through a constant linear

[20] Probability weighting function explains why the same person prefers to buy an insurance (risk averse behavior) and at the same time he also prefers to buy a lottery (risk seeking behavior).

relationship. Therefore, choices δ_i^* can be specified over each individual, and this can be denoted as:

$$\delta_i^* = \theta_0 \;+\; \theta X_i; \qquad \forall_i, \tag{3.13}$$

where θ_0 and vector θ are coefficients to be estimated given the binary choice of lottery A and B, the following latent regression model can describe this.

$$\delta_i^* = \Delta_i^{CPT}(X_i) + \varepsilon_i = \theta_0 \;+\; \theta X_i \;;\; \forall_i, \quad \text{and} \qquad \delta_i = \begin{cases} A \text{ } if \text{ } \delta_i^* > 0 \\ B \text{ otherwise} \end{cases}$$

Where ε_i is normally distributed error term with mean zero and variance 1. Further, to derive the probability that subject *i* will choose lottery A from the above equation;

$$\begin{aligned} \Pr(\text{choose lottery } A|\, Xi) &= Pr\,(\Delta_i^{CPT}(X_i) + \varepsilon_i > 0|\, Xi) \\ &= 1 - Pr\,(\varepsilon_i \leq -\Delta_i^{CPT} \mid X_i) \\ &= 1 - \phi\,(-\Delta_i^{CPT}(Xi)) \\ &= \phi\,(\Delta_i^{CPT}(Xi)), \end{aligned} \tag{3.14}$$

By denoting Δ^{CPT} the difference in prospect utilities, the likelihood of the observed choices, conditional on our CPT specification being true, is written as follows;

$$Ln\, L^{CPT}(\delta, X; \theta, \gamma, \alpha) = \textstyle\sum_k [ln\, \phi(\Delta^{CPT}{}_k) \times I(\delta_k = A) + ln[1 - \phi\,(\Delta^{CPT}{}_k)] \times I(\delta_k{=}B)] \tag{3.15}$$

where, k is the index of lottery choices pooled of subjects, I is the indicator function, and δ_k denotes the choice of lottery A or B. Finally, the maximum-likelihood estimation for the risk parameter is, therefore:

The maximum-likelihood estimation for (θ, γ, α)) is then;

$$(\theta^{\wedge}, \gamma^{\wedge}, \alpha^{\wedge}) = \arg\max\, ln\, L^{CPT}(\delta, X; \theta, \gamma, \alpha). \tag{3.16}$$

It should be mentioned that the original experiment by HL is such that any combination of choices determines a particular interval for the CPT parameter values. It is also worth mentioning that both these models estimate the parameters through maximum likelihood estimation. The estimation procedure was conducted in STATA software; the underlying models are defined in both scenarios.

3.5 Survey Area and Data Description

This study was conducted in Madhya Pradesh, the second-largest state by area, situated in central India. The state has been at the forefront of agricultural growth in the last decade (Gulati et al., 2017). We selected three villages based on our convenience and accessibility to rural areas in the Rewa district. In all these villages, the residents' primary occupation was agriculture, which was the primary livelihood source. The selected villages are Pakara, Chandeh, and Balmukunda. Given that this study was conducted in rural India, where most farmers were not educated, the researcher filled out questionnaires based on the information provided by the respondents. Furthermore, the game was designed in a pictorial format using black and red balls to represent probability values, aiming to enhance the participant's understanding of the experiment. The study included 121 respondents.

To summarize the characteristics of both the farms and the farmers, Table 2 presents relevant variables in the form of summary statistics. It is important to note that we included only the head of the household, who makes all agricultural-related decisions. The survey data collected for the study reveal that the average age of the respondents was 46.04 years, with a predominance of males (93.39 percent). Therefore, the gender variable was excluded from the model due to the limited representation of females. The sample statistics show that approximately 62.81 percent of the farmers had no formal education, around 30 percent had completed only primary school, and the remaining 7.44 percent had received a college education.

The mean family size reported was 8.36, with an average of 3.42 people actively engaged in regular agricultural activities. The approximate annual household income had a mean value of 4.36 Lakhs, with a standard deviation 3.69. Additionally, the mean number of children in each household was reported as 2.89, with a standard deviation 1.3. The average household expenditure on education was reported to be 0.6 Lakhs, with a standard deviation of 0.7. We included the number of children and education in our study, as farmers perceive these factors as long-term investments and connect them to the causes of risk-seeking behavior (Maertens et al., & Just, D. R., 2014).

Table: 3.2 *Summary Statistics of Farmers and Farm Characteristics*

Farmers Characteristics	Mean/Percentage	Sd. Dev.
1. Age (Years)	46.04	9.34
2. Gender (male=1; female=2)	93.39% Male	
3. Education (in %)		
A. No Edu	62.81%	
B. School edu (up to 12th)	29.75%	
C. College edu	7.44 %	
4. Household Size (nos.)	8.36	2.76
5. People involved in agriculture (nos.)	3.42	1.66
6. Children in household (nos.)	2.89	1.30
7. No of years involved in agri activities (years)	23.66	11.32
8. Decision-maker involves other family members in decision-making (%)		29.75
9. Number of Rooms in Household (nos.)	5.01	2.39
10. Farm size (acres)	2.87	2.25
11. Land lease (acres)	0.33	0.81
12. Annual Household Income (Lakhs)	4.36	3.69
1 if 0 to 100000		
2 if 100001 to 200000		
3 if 200001 to 300000		
4 if 300001 to 400000		
5 if 400001 to 500000		
6 if 600001 to 700000		
7 if 700001 to 800000		
8 if 800001 to 900000		
9 if 900001 to 1000000		
10 if 1000001 to above		
13. Total expected farm income (Lakhs) (Similarly defined as Annual Family Income)	2.19	1.20
14. Household education expenditure (Lakhs)	0.60	0.70
15. Livestock (nos.)	3.65	2.87
16. Credit from formal sources (%)	28.93	
17. Credit from formal sources (%)	39.57	

This study also examines the involvement of friends and family in decision-making. We queried the primary decision-maker about their practice of including other family members in farm-related decision-making processes. It was revealed that 29.75 percent of the subjects reported involving their family members in these decisions. Such behavioral traits can contribute to the potential for improved decision-making. This behavior may be particularly effective in enhancing decision quality, especially among those without formal education.

Regarding farm-related characteristics, respondents were also asked to indicate the number of years they have been engaged in agricultural activities. The study found that, on average, respondents had been involved in agricultural activities for approximately 23.66 years. Additionally, we considered various wealth indicators for each family, including the number of rooms in the household, farm size, leased land, annual household income, farm income, livestock ownership, and formal and informal credit access. These wealth indicators play a crucial role in shaping individual decisions. Holden et al. (1998) discussed the concept of the substitutability constraint among different types of assets, highlighting that such constraints within the wealth category have an independent impact on risk behavior. In a recent study, Yesuf & Bluffstone (2009) also analyzed the role of various asset types and their relationship with risk behavior among impoverished Ethiopians.

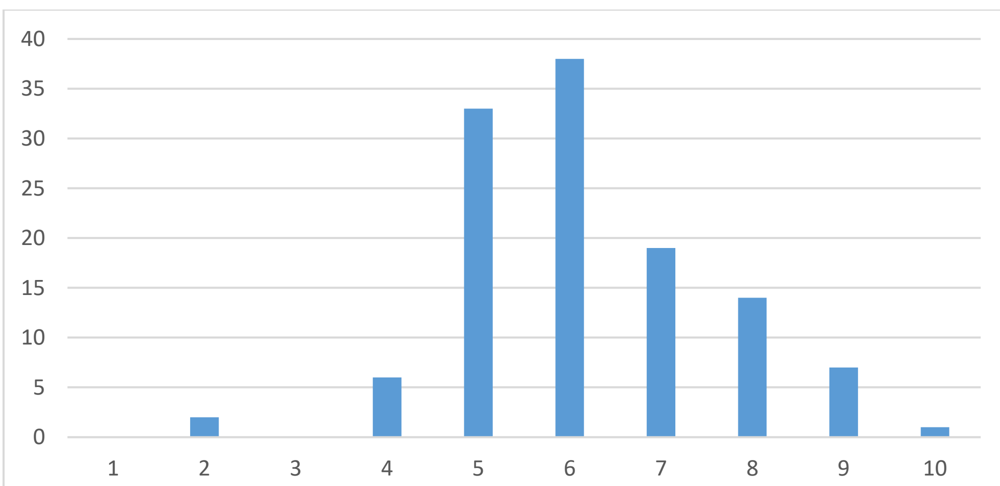
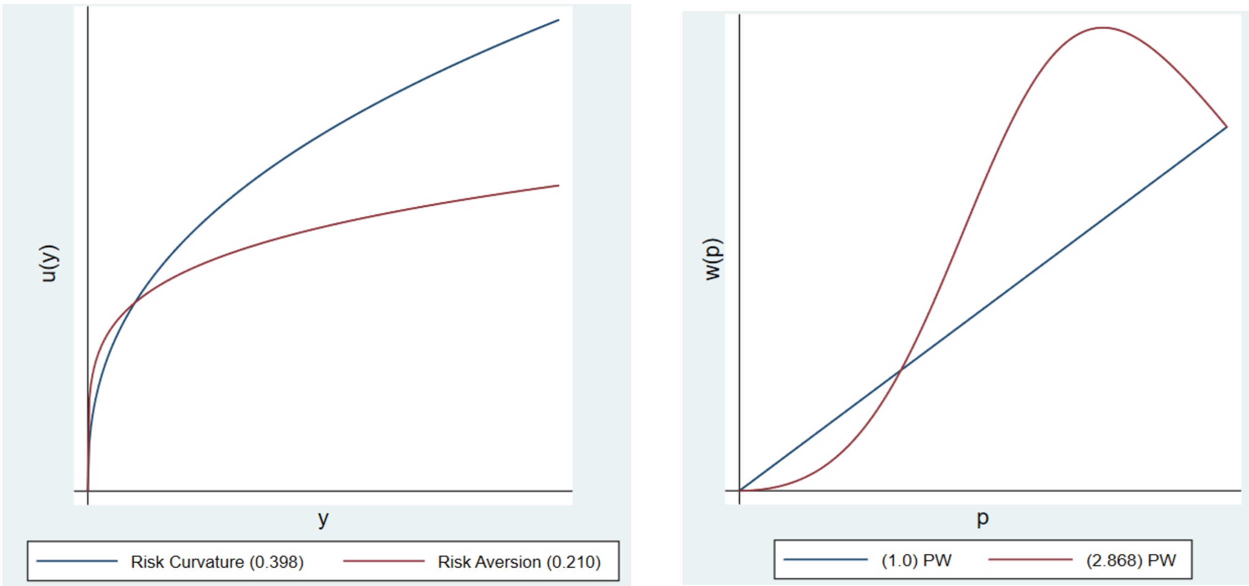


Figure: 3.1 *Choice rows where respondents switched from lottery A to lottery B*

Table: 3.3 Estimated Parameters of EU and CPT Models without Explanatory Variables

Parameters	**Estimated Values**
Risk Aversion (r_{EU})	0.392*** (0.015)
Risk curvature (α_{CPT})	0.210*** (0.011)
Prob. Weighting (γ_{CPT})	2.868*** (0.128)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
r_{EU}: constant =1 0.0000; α: constant =1 0.0000, γ: constant =1 0.0000



a b

Figure: 3.2 *Shape of Utility Curvature and Probability Weighting*

Table 3.4 *Factors Determining Risk Parameters*

Variables	Expected Utility Model	Prospect Theory Model	
	r_{EU}	α_{CPT}	γ_{CPT}
Age	0.079***	-0.026	-0.324
	(0.029)	(0.018)	(0.402)
No Education	0.042	0.070	-0.354
	(0.051)	(0.051)	(1.279)
School education	0.179**	0.103*	0.115
	(0.073)	(0.054)	(1.477)
Household Size	-0.022	-0.004	-0.048
	(0.015)	(0.009)	(0.597)
Number of Persons in	0.056**	0.008	0.050
Agricultural Activities	(0.025)	(0.010)	(0.200)
Children in Household	0.013	-0.0121	0.228
	(0.020)	(0.010)	(0.335)
Years in Agricultural	-0.095***	0.015	0.280
Activities	(0.029)	(0.016)	(0.449)
Family Participation in	0.265***	-0.714***	114.0***
Decision Making	(0.079)	(0.067)	(11.74)
Household Income	0.021	0.0175**	0.037
	(0.018)	(0.007)	(0.166)
Agricultural Income	-0.049***	-0.008	0.288
	(0.019)	(0.020)	(0.372)
Household Education	-0.009	0.0001	0.0320
Expenditure	(0.014)	(0.009)	(0.451)
Farm Size	0.017	-0.005	0.082
	(0.011)	(0.012)	(0.292)
Lease land	0.041**	-0.003	0.575
	(0.020)	(0.014)	(0.813)
Livestock	0.006	-0.002	0.104
	(0.007)	(0.006)	(0.118)
Formal debt	-0.210**	0.715***	-114.8***
	(0.107)	(0.071)	(11.74)
Informal debt	-0.076***	0.017	-0.161
	(0.027)	(0.025)	(0.808
No. of Rooms	-0.025*	-0.012	-0.148
	(0.014)	(0.010)	(0.714)
Constant	0.276**	0.286***	3.170*
	(0.113)	(0.089)	(1.693)
Observations	1,210	1,210	1,210

Robust standard errors in parentheses

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

r_{EU}: constant =1 0.000; α: constant =1 0.0001, γ: constant =1 0.0000

3.6 Results

First, we analyze the expected utility model, assuming that the power specification for the utility curvature parameter solely reflects risk behavior. Next, prospect theory utility with two parameters, risk curvature, and probability-weighting, describe risk behavior is discussed. Both models are presented in Section 3.4. It is worth mentioning that we have not included the loss scenario in the experiment. Therefore, we have excluded the loss aversion behavior in this model. In the first case, assuming the EU model, the parameter r_{EU} controlling utility curvature alone explains choice behavior. We assume that individual characteristics determine risk behavior and have linear relationships. The study's main result can be drawn from Table 3.3 and Table 3.4. Results reflect that under the EU model, the mean value of risk aversion parameters among farmers was 0.392. The estimated parameter is statistically significant at the 0.000 level. This indicates significant concavity in the utility curvature. Comparing the EU utility model with the CPT specification utility function, also called value function, parameter α_{CPT} found that the estimated value function is significantly low, 0.210, and statistically significant at 0.000. A value function is a psychological representation of individual behavior in the gains domain. We can see a significant variation in the utility curve in Figure 3.1a. It can compare the utility curvature of both these parameters. A value function is a proxy of the utility curve, and these parameters are comparable. The CPT model reflects that the decision-makers are highly risk-averse and that farmers prefer a relatively stable return. This result suggests that farmers are highly risk-averse and more likely to prefer stable returns.

Now, observing the likelihood sensitivity parameter γ_{CPT}, the estimated value parameter was 2.868 and also statistically significant at level 0.000. This reflected significant subjective distortion in given probabilities. The value of the probability weighting parameter is presented in the pictorial depiction in Figure 3.1(b) as an s-shape curve. It is likely similar to an S-shaped curve, as de Brauw & Eozenou (2014) estimated with aggregated data from Mozambique farmers. It denotes that a farmer under-weighted small probability and over-weighted large probability. Contrary to Tversky and Kahneman's (1992) argument, large probabilities are under-weighted, and small probabilities over-weighted by decision-makers. This might further need to examined in the scenarios, in which, farmers prefer to overemphasize the large probabilities, rather than small probabilities; or it may be due to the experimental design, in which probabilities were systematically changing and precisely equal in both games and farmers' extreme risk aversion behavior.

Next, analyzing the determinants of risk behavior, we test whether these explanatory variables are significant in explaining risk behavior through risky experimental lotteries. Under the expected utility model of decision-making, it can be seen that respondents with school education, age, family participation, and land lease behavior are statistically significant variables that determine the risk curvature. These variables are positively associated with the risk-aversion parameter, meaning that farmers are less risk-averse with increase in their age, education increase, family participation, and land lease. Further, farmers' agricultural experience, income, and formal and informal debt were statistically significant and negatively associated. It reflects that when farmers' experience and income increase, farmers are less likely to take risk.

Considering the prospect theory model, it reflects that farmers' individual characteristics do not explain the risk curvature and probability distortion behavior, even though result reflects that farmers are highly risk-averse and sensitive to the probability distortion. The result shows that farmer's individual characteristics are not statistically significant, except for school education, and farmers' behavior of family participation in decision-making. The study finds that farmers' behavioral characteristic of allowing other members in the decision-making is a significant behavioral characteristic to explain risk behavior. Comparing to the farmers that do not allow to the other family member in the decision-making, such farmers are more risk averse and highly sensitive to the probability distortion.

Further, this study included different wealth indicators, i.e., household and agricultural income, education expenditure, formal and informal debt and numbers of room in the home. We found that only household income and formal debt are statistically significant and positively associated.

Finally, to observe the determinants of the risk curvature parameter, this study found that variables i.e., school education, farmers' behavior about family participation in decision-making, and formal debt are significant in determining the risk curvature. It denotes that school educated farmers are less risk-averse compare to the farmer having no education or college education.

3.7 Discussion and Conclusion

Assessing risk preferences is crucial to better understanding individual decisions. Various risk preference elicitation methods are available to elicit risk preference. The role of the experimental method has increased over the last decade and has become the most prevalent method. This is a hypothetical and non-hypothetical lottery choice (Eckel & Grooman, 2008; Holt & Laury, 2002); one of the better experimental methods for capturing risk behavior. It is hard to say what is the best risk preference elicitation method to predict actual risk behavior. However, Dohmen et al. (2011) argued that it is a simple and easy method that best explains real-world risky behavior. Now, comparing our findings with other studies in developing countries, Indian farmers exhibit a higher risk aversion than studies conducted on Chinese and Vietnamese farmers. In another study on West African farmers, the study concluded contrary results. Regarding probability weighting distortion, Indian farmers follow a similar pattern to other Asian countries.

Further, this study is consistent with other studies among the poor, as poor farmers are more risk-averse. This denotes that poverty positively correlates with risk aversion (wik et al., 2004; Yesuf & Bluffstone, 2009; Binswanger, 1980; Liebenehm & Waibel, 2014). However, some studies concluded that poverty has no significant correlation (Tanaka et al., 2010).

Table: 3.5 *Comparison of Estimated Risk Parameters from Various Studies in Developing Countries*

No.	Studies	Risk aversion	Prob. Weighting
1.	Liu (2013) China	0.48	0.69
2.	Tanaka Camerer & Nguyen, (2010) Vietnam	0.59	0.74
3.	Nguyen & Lguyen (2010) Vietnam	0.62	0.75
4.	Liebenehm and Waibel (2014) W. Africa	0.112	0.133
5.	de Brauw & Eozenou, (2014) Mozambique	0.33	1.37
6.	The present study	0.21	2.868

As farmers' characteristics regarding age and education are significant determinants in risk behavior, our results are different from previous studies that elderly farmers are more risk averse than younger farmers (Yesuf & Bluffstone, 2009; Liebenehm & Waibel, 2014; de Brauw & Eozenou, 2014). In this study, it is important to note that farmers mainly reported no education or school education. We have not captured cognitive ability through direct measurement. It might suggest a possibility of less analytical ability among respondents given the lower level of education. Some studies suggest an important linkage between risk preferences and cognitive abilities (Dohmen et al., 2010). A lower cognitive ability is associated with less risk-aversion behavior. Unlike uneducated farmers, this study found that educated respondents were highly sensitive to probability distortion.

Given the importance of risk attitude and perception in risk behavior decision-making, this study found a significant role of probability weighting in better decision-making. This study tried to approach capture collective decision-making, including family members in the decision-making. It is an indicator of human capital that may help improve the decision quality among farmers. A potential risk management strategy is derived from the individual capacity, i.e., available resources, information, government policies, and regulations. In this view, including other people in decision-making may improve the quality of the decision.

Moreover, if a decision-maker is more accurate in assessing probability information, he can make better decisions considering their differences and capacities. A decision-maker may also understand and utilize various policy initiatives, i.e., risk-mitigating tools such as price intervention, price stabilization, export subsidies, and insurance schemes. Farmers change their behavior with the best possible options given these policy initiatives. For example, minimum support prices, credit incentive schemes, Subsidized seed distribution, and agricultural insurance schemes are important policy initiatives that a farmer should emphasize accurately during decision-making.

Debate on determinants of risk behavior is useful for the asset integration hypothesis. To what extent subjects integrate their potential wealth and income into the risk behavior is another important debate. Can lottery decisions in the experimental setting identify actual risk behavior if a participant faces small and large payoffs? Heinemann (2008) argued that increasing the experiment's stakes might help to capture actual risk behavior, but he also concluded in his study that wealth could not fully explain risk behavior. More recently, Andersen et al. (2018) also concluded partial asset integration behavior and argued that individual wealth could be a closer substitute for experimental income.

Finally, the study concludes that an artefactual field experiment is a simple and easy method of assessing risk attitude. We examined the result of two models that explain individual risk behavior. A leading model to analyze risk behavior, expected utility theory is most commonly applied method. An alternative model of "Cumulative Prospect Theory" is another emerging method, perhaps a better model for understanding risk phenomena in the real world. It captures individual biases, which is essential in understanding risky decision-making. This study also concludes that wealth indicators cannot fully explain risky behavior and are perhaps crucial in understanding biased behavior in real-world decisions. In other words, subjectivity is eminent in risky decision-making; people might willingly deviate from the expected utility. Policymakers must incorporate behavioral responses of the targeted population in essential policy formulation for the effectiveness of development programs.

Chapter 4

Risk Attitude and Response to MSPs in Production Decision among Farmers: A Cumulative Prospect Theory Approach

4.1 Introduction

Agriculture constitutes an inherently risky economic endeavor, posing an ongoing challenge to predict farmer behavior when making agricultural decisions accurately. Risk stems from diverse sources, each with varying degrees of impact and corresponding assessment methodologies. A farmer's risk perception is inherently subjective, directed by their varied exposure to various sources. This subjectivity significantly influences the subsequent production decisions. Both risk attitude and perception exert influence over a farmer's strategic choices. This translates to a farmer's preference for cultivating crops that promise enhanced future returns or yield relatively stable profits while entailing lower levels of risk.

The decision-making process governing agricultural production undertaken by a farmer is considerably more intricate. Factors such as forthcoming opportunities within the immediate time and potential avenues for mitigating risk play a pivotal role in shaping these decisions. Consequently, comprehending how farmers respond to risks across various contexts—ranging from the selection of crops, adoption of technological innovations, production management, and addressing climatic vulnerabilities to making informed choices regarding insurance—are areas of profound economic significance.

In a high-risk environment in the developing world, governments often implement agro-incentive schemes to support agriculture. These incentives encompass input subsidies (such as seeds, fertilizers, electricity, and technology) and output subsidies (including price incentives, transportation assistance, and storage capacity enhancement). This study focuses on a particular form of output subsidy known as the 'Minimum Support Price (MSP); which stands as one of the prominent tools for agricultural assistance in numerous developing countries, including China, India, Pakistan, Brazil, and Thailand. The MSP plays a pivotal role in stabilizing prices for farm products, particularly pertinent to pre-production decisions.

For instance, the government of India announces MSPs[21] across 23 different crops every year, providing it in the form of 'contingent subsidies.' The primary goal of MSPs is to ensure price stability by dictating a predetermined price for products before the commencement of production decisions. This mechanism serves as a safeguard: if the market price of a crop falls below the MSP, the government intervenes by purchasing the crop at the stipulated MSP. This assurance of a minimum price is a compelling incentive for farmers to include the relevant crop within their production portfolio.

Beyond its role in price stabilization, the MSP also ensures responsibility for maintaining a strategic buffer stock of food grains. To achieve this, the government undertakes substantial procurement of food grains, guaranteeing availability to vulnerable sections of society at subsidized rates. This twofold function of MSP—price stabilization and buffer stock maintenance—resonates as a significant means by which governments in the developing world manage agricultural risk and ensure food security.

This study delves into the impact of individual risk attitudes on production decision-making. Recent research has brought attention to the efficacy of Minimum Support Prices (MSPs), suggesting that implementation of MSPs may be contributing to regional disparities (Ali et al., 2012; Tripathi, 2012) and that it tends to favor specific crops—primarily rice and wheat (Chhatre et al., 2016; Mittal & Hariharan, 2016). Furthermore, certain contemporary studies have raised concerns regarding the socioeconomic and environmental contexts that lead farmers to prefer sub-optimal choices (Gupta et al., 2021).

[21] Government of India announces MSP for 23 crops, which consist of seven cereals (Paddy, wheat, maize, sorghum, pearl millet, barley, ragi), seven oilseeds (peanut, rapeseed, soyabean, sesame, sunflower, safflower, nigerseed), five pulses (gram, tur, moong, urad, lentil), and four commercial crops (sugarcane, cotton, copra, and jute).

A counter-argument in favor of MSPs asserts that the announcement of MSPs yields positive impacts on market prices. It is important to note that the government's role in MSPs does not always involve direct procurement of all MSP-designated crops from farmers. Instead, the government sets a base price that provides farmers a foundation for trade negotiations. Within this framework, MSPs work as reference prices that ultimately facilitate equitable price realization.

In the realm of limited risk mitigation strategies in production decisions, producers face three choice scenarios for crop selection to manage price risk. Within this context, considering a 'strategic farmer' who possesses comprehensive awareness of all items within the production portfolio, it becomes evident that their choices reflect their risk-bearing capacity and individual perspectives on risk mitigation strategies. Our analysis of farmers' risk behavior within agricultural decision-making stems from the recognition that the intrinsic behaviors of individuals fundamentally support the efficacy of Minimum Support Prices (MSPs) in influencing production decisions.

Farmers are presented with three primary options for their course of action. First, they may opt to exclusively cultivate items the government procures at predetermined minimum prices established by MSPs. Second, they might choose to cultivate items that fall outside the scope of MSP procurement, inherently exposing these products to the open market's greater price volatility. The third option entails diversifying its produce, encompassing both MSP-supported items and those beyond its purview, moderating their risk preferences.

Hence, within the framework of this policy that seeks to diminish risk mitigation strategies, we scrutinize the behavioral response of MSPs within decision-making processes characterized by risk and uncertainty. Notably, there is a dearth of research within the Indian context regarding exploring producers' risk preferences in decision-making. The present study fills this void by contributing to the existing literature by documenting farmers' behavioral reactions to MSPs throughout the decision-making process.

The chapter is structured as follows: Section 4.2 provides an introduction of prospect theory and section 4.3 provides an overview of past studies on farmers' risk behavior using prospect theory model. Section 4.4 deals with prospect theory model and section 4.5 describe the experimental design and procedure. Section 4.6 deals with estimation of different parameters of prospect theory.

Section 4.7 describe the data collection process and sample characterization and 4.8 outlines econometric method used in this study. Section 4.9 deals with the result of this chapter followed by subsequent discussions and conclusions in sections 4.10 and 4.11, respectively.

4.2 Introduction of Prospect Theory

A substantial body of literature encompasses diverse contexts within developing countries to comprehend the diversity inherent in risk preferences and its impact on agricultural decision-making. Binswanger (1980, 1981) stands among the pioneers who endeavored to elicit farmers' risk behaviors via experimental methodologies. In his approach, Binswanger employed a combination of real and hypothetical lottery scenarios to unveil underlying preferences and points of departure in farmers' overarching risky decisions. Other studies used alternative methods; studies opted for an econometric method grounded in actual data (Antle, 1987; Bardsley & Harris, 1987; Bar-Shira et al., 1997; Chavas & Holt, 1996; Moscardi & de Janvry, 1977). While these methods diverge considerably in their underlying assumptions, they are collectively underpinned by a shared theoretical foundation—Expectation of Utility Maximization (EU theory)

Despite the prevalence of the Expected Utility (EU) theory[22], an alternative framework, known as Cumulative Prospect Theory (CPT), has gained attraction as a burgeoning methodology (Quiggin, 1982, 1991), offering novel perspectives within the theoretical framework. Cumulative Prospect Theory represents a refined iteration of the earlier prospect theory. Unlike the traditional EU theory, which hinges on expected utility based on absolute wealth and assumes uniform behavioral responses at all wealth levels, CPT introduces cumulative decision weights that fluctuate across distinct levels of wealth.

In contrast to the single parameters employed in the Expected Utility (EU) model, Cumulative Prospect Theory (CPT) formulates utility curvature about a reference point, categorizing outcomes as gains or losses. This reference-dependent approach results in varying responses within the gain and loss domains (Tversky & Kahneman, 1992). Furthermore, in addition to evaluating an extensive analysis of risk preferences, CPT also incorporates subjective judgments regarding prospects—instances where individuals may assign higher significance to certain prospects more

[22] A conceptual framework to formulate risk preferences, alternative model gain popularity because of its simplicity in the application. Another advantage of this model was that it clearly distinguished risk exposure and risk preferences in terms of probabilities and utility function (Chavas et al., 2010).

than likelihood. Consequently, CPT offers a comprehensive framework for analyzing risk, encompassing risk sensitivity, loss aversion, and probability weighting considerations.

The conventional approach of rigidly assuming a single-parameter model offers limited flexibility compared to alternative models. Prospect theory (PT) and rank-dependent utility models, which introduce enhanced behavioral considerations, stand as such natives. One prominent alternative, prospect theory (PT), was introduced by Kahneman & Tversky (1979), wherein the utility function is delineated separately for responses to gains and losses. Empirical testing of this theory involved the examination of a probability weighting function, which subjectively converts the underlying probability of a lottery into a subjective probability. This model strongly emphasizes subjective behaviors, thereby accommodating the incorporation of behavioral phenomena like biases and learning within the framework.

4.3 Role of Prospect Theory in Farmers' Agricultural Decision

Cumulative Prospect theory proves more adept at elucidating risky behaviors in scenarios where farmers potentially modify objective probabilities through a heuristic process of probability weighting. This transformation of probabilities occurs during the assessment of prospects, where decision-makers tend to magnify the significance of small probabilities and downplay that of larger probabilities—a phenomenon recognized as probability weighting (Quiggin, 1981). Additionally, the inclination towards risk may also vary by a reference point. Decision-makers exhibit risk aversion for prospects associated with risk in the gain domain and shift towards risk-seeking behavior for prospects in the loss domain.

A comparative analysis between Prospect Theory (PT) and Expected Utility (EU) theory reveals that PT offers a superior explanation for various risky phenomena (Bocquého et al., 2014; Bellemare et al., 2020). Nguyen and Leung (2009) explored the risk preferences of Vietnamese fishermen through CPT, discovering that fishermen exhibit comparatively lower risk aversion and reduced sensitivity to changes in probability weighting compared to individuals from other occupations. Tanaka et al. (2010) conducted an experiment with 181 Vietnamese farmers, found statistically significant CPT parameters, and revealed that loss aversion and risk aversion behavior are inversely influenced by wealth.

Liu and Huang (2013) applied a CPT model to investigate the impact of risk preferences on pesticide use among cotton producers in China. Their findings indicate that farmers exhibiting greater risk aversion and lower loss sensitivity tend to favor higher levels of pesticide usage. Meanwhile, within the European context, Bocquého et al. (2014) evaluated the risk preferences of 111 French producers using both EUT and CPT. Their study affirmed the presence of concave utility curvature as captured by EUT and revealed significant parameter estimates for loss aversion and probability distortion behavior.

Recently, several studies have approached examining demand through the lens of behavioral economics. For instance, the work by Elabed & Carter (2013) constructed a model to investigate how the perception of basis risk impacts the demand for index insurance among farmers in Mali. Their study differed from the expected utility maximization framework, as farmers were willing to pay premiums exceeding the average for index insurance. This behavior deviated from conventional expectations.

Similarly, Zhao & Yue (2020) explored the perception of indemnity in crop insurance decisions among farmers in the USA. Their study found significant disparities in the perception of indemnity. The study found that variation was driven by instances of objective probability distortion, further highlighting the influence of behavioral factors in shaping insurance-related decisions.

Cumulative Prospect Theory (CPT) has been applied in various decision-making studies in agricultural production. One notable example is that farmers often resist paying modest crop insurance premiums, instead opting for relatively higher risks. Even if it entails the potential for larger losses. This pattern becomes evident in cases such as the voluntary crop insurance program, wherein only 25 percent of eligible farmers prefer to participate, despite a generous 30 percent premium subsidy offered by the government under the Federal Crop Insurance Act of 1980 (Glauber et al., 2002; Glauber, 2013).

Similarly, in the context of Indian farmers, Chintapalli & Tang (2022) delved into the decisions of farmers in response to Minimum Support Prices (MSP) as a risk-mitigating tool. The study categorized farmer's behavior as myopic or strategic based on their decision-making approaches. Myopic farmers make crop production decisions on the basis of recent or current market prices. In contrast, strategic farmer accounts for prospects while considering the strategies of other players within the production sphere. These behavioral discrepancies between farmers arise from variations in risk attitude and individual perception. Interestingly, farmers who solely consider prevailing market prices in their decision-making assume heightened risks, even when an alternative option of stable prices exists. This deviates from the expectations of Expected Utility Theory (EUT), which assumes the underweighting of potential losses in decision-making. This underlines the importance of examining farmers' risk behavior in the context of policy tools like MSPs, as it holds significance for policy effectiveness. Furthermore, Hu et al. (2019) explored the role of strategic farmers. They found that their presence often results in a general reduction of market prices, driven by their ability to anticipate rationality within production decisions.

Crop selection and the associated risks exhibit notable variations within the framework of production decisions. Assuming a risk-averse inclination, a decision-maker typically gravitates towards items entailing comparatively lower levels of risk within their production portfolio. However, the decision-making process undertaken by farmers in terms of crop selection is also strategically driven. These farmers engage in strategic anticipation; they are informed of current crop production conditions but also by the responses of other farmers throughout the production season.

Minimum Support Prices (MSP) are pivotal in reducing price volatility, enabling farmers to make more informed choices when choosing their production portfolios. As a result, the selection of crops for cultivation is inevitably influenced by the presence of MSPs. Consequently, cropping patterns emerge as a crucial aspect impacted by adopting MSPs.

The influence of Minimum Support Prices (MSPs) on farmers' crop selection within the production decision remains a less-explored area in the existing literature. Within this decision-making process, the behavioral response of a farmer is important. Adopting MSP for a major share in total production can potentially curtail the anticipated benefits a farmer would reap by exclusively cultivating crops covered by MSPs. This scenario may unfold when most farmers prefer to cultivate MSP-supported crops (Chintapalli & Tang, 2021). This behavioral trend arises from farmers' heightened responsiveness to risk-averse preferences during the decision-making.

This study extends the proposition that, in view of MSPs serving as risk-mitigating tools within the production decision, farmers are influenced by risk-mitigating strategies. For instance, a farmer characterized by pronounced risk aversion could exhibit heightened sensitivity to the impact of MSPs and opt solely for crops backed by MSPs. Conversely, farmers with a more moderate risk aversion might prefer a diverse assortment of crops within their cultivation portfolio.

4.4 Prospect Theory Model

The theoretical framework of this study assumes that an individual agent elicitation process follows prospect theory. It encompasses broader risky behavioral characteristics, including expected utility theory, a particular case of prospect theory. It covers additional behavioral characteristics, like loss aversion and probability distortion. Applying the expected utility model might overlook these additional risk behavior characteristics. In this study, we used cumulative prospect theory, assuming that the utility function follows two sets of power specifications adapted from Tversky & Kahneman (1992):

$$u(y) = \begin{cases} y^{\alpha} & if\ y \geq 0 \\ -\lambda(-y)^{\alpha} & if\ y < 0 \end{cases} \tag{17}$$

Where y is a lottery payoff, and α is a risk-aversion measure reflecting the utility curvature. In the gain scenario, α must be greater than 0, and all payoffs must be greater than 0 in the experiment. It implies that the utility function is risk-seeking (convexity) if $\alpha > 1$, risk-neutral (linear) if $\alpha = 1$, and risk-averse (concavity) for $\alpha < 1$. Because it is considered that the utility function is symmetrically concerning to 0, the interpretation of α for gain is also reflected for losses. Further, λ is the coefficient for loss aversion if $\lambda > 0$. If $\lambda > 1$, the decision-maker is more sensitive to losses of similar gains and vice versa.

The experimental data applying prospect theory is a well-arranged increasing ordered payoff, where y_1 and y_2 are the payoffs, and p and 1- p are the respective probabilities. In the risk elicitation process, individuals make consecutive choices between lottery choices. The cumulative prospect theory can be defined for each lottery choice in a particular row j, given probabilities and respective payoffs, integrating the values function and probability weights. It can be shown as follows:

$$\text{CPT} = \begin{cases} w(p)\, u(y_1) \,+\, (1 - w(p)) \,*\, u(y_2) & if\ y_1 \geq\ y_2 \geq\ 0 \text{ (gain)} \\ & or\quad y_1\ \leq y_2 \leq 0\ (loss) \\ w(p)\ * u(y_1)\ +\ w\ (1 -\ p)\ *\ u(y_2) & if\ y_1 < 0 < y_2 (mixed) \end{cases} \quad (18)$$

The above function $w(p)$ represents probability weighting. We use Prelec (1998) probability weighting function as follows:

$$w(p) = \exp\left[\ - (-\log p)^{\gamma}\right] \quad (19)$$

This probability weighting model captures the curvature of probability weighting γ, which will be estimated. When $\gamma < 0$, the probability weighting function followed the inverse-S shape. It can be interpreted as individual overweight small probabilities and underweight large probabilities. If $\gamma > 0$, the weighting function follows the S-shape, individual underweight small and overweight large probabilities. It is also worth mentioning that if $\gamma = 1$, mean individuals do not distort probabilities, and this linear probability function is equal to the expected utility theory.

4.5 Experimental Design and Procedures

The experimental method incorporating Prospect Theory finds widespread application in diverse contexts to observe risk preferences within agricultural decisions. It is known as the TCN approach, this method has been employed in various studies to explore risk preferences (Bocquého et al., 2014; Bougherara et al., 2017; Liu, 2012; Liu & Huang, 2013; Reynaud & Couture, 2012; Zhao & Yue, 2020). This method draws inspiration from the well-known study by Holt & Laury (2002), which introduced an experimental framework featuring multiple price lists.

The TCN approach encompasses three series of lottery-choice decisions—lottery options A and B against each other—akin to a variant of Holt and Laury's procedures. Additionally, it facilitates a systematic relative comparison between two risky binary lotteries. This method stands as an effective means of investigating risk preferences in a controlled and structured manner.

It has recently gained prominence as a popular risk elicitation method for estimating the structural model of Prospect Theory (PT) utility. This experimental approach entails a configuration of lottery choices within a unique design that offers participants an array of choice set combinations. This design is adept at capturing distinct values of PT parameters, contributing to its relevance.

Table: 4.1 *TCN Experimental Lottery Series*

	Lottery A		Lottery B	
	Prize A1	**Prize A2**	**Prize B1**	**Prize B2**
Prob.→	30%	70%	10%	90%
1	400	100	680	50
2	400	100	750	50
3	400	100	830	50
4	400	100	930	50
5	400	100	1060	50
6	400	100	1250	50
7	400	100	1500	50
8	400	100	1850	50
9	400	100	2200	50
10	400	100	3000	50
11	400	100	4000	50
12	400	100	6000	50
Prob.→	90%	10%	70%	30%
1	400	300	540	50
2	400	300	560	50
3	400	300	580	50
4	400	300	600	50
5	400	300	620	50
6	400	300	650	50
7	400	300	680	50
8	400	300	720	50
9	400	300	770	50
10	400	300	830	50
11	400	300	900	50
12	400	300	1000	50
13	400	300	1100	50
14	400	300	1300	50
Prob.→	50%	50%	50%	50%
1	250	-40	300	-210
2	40	-40	300	-210
3	10	-40	300	-210
4	10	-40	300	-160
5	10	-80	300	-160
6	10	-80	300	-140
7	10	-80	300	-110

The present study is organized into a series of three choice sets, encompassing 33 pairs distributed across two games. Series one and two comprise 12 and 14 pairs of lottery choices, respectively, while series three consists of 7 pairs of lotteries featuring negative payoffs. The experiment is subdivided into two lottery series—A and B. In lottery A, payoffs and their corresponding probabilities remain consistent throughout series one and two. This lottery experiments a deliberate pattern wherein a single payoff in each row deviates in lottery series one and two. Such a meticulous experimental design enhances clarity and facilitates the comprehensive capture of broad behavioral characteristics.

The experimental design involved subjects making choices between two lotteries, A and B, within each row. Participants were informed that they could switch from lottery A to lottery B once in each series, a provision introduced to maintain the principle of monotonicity. This condition ensured that subjects' preferences adhered to a consistent pattern.

For individuals exhibiting high levels of risk aversion, the likelihood of opting to switch from lottery A to B would be minimal. Conversely, a respondent demonstrating a propensity for risk-seeking behavior would consistently favor the riskier lottery, preferring lottery B in all instances. In contrast, risk-neutral participants would decide to switch lotteries in the seventh row, motivated by the fact that the expected value of lottery A diminishes in comparison to lottery B.

We employed a visual presentation format to enhance the clarity and facilitate participants' comprehension of these lottery series. The lottery series was rendered in a pictorial form, featuring a distinctive color scheme. Specifically, we utilized red and black balls to represent the lotteries, as depicted in the questionnaire provided in the appendix. This color-coded approach ensured that the numbers of red and black balls were prominently discernible, allowing participants to identify and associate probabilities during the experimental procedures readily.

The experiment was individually conducted at the residences of the respondents. To initiate the process, we enlisted the help of local support to contact the respondents. Our initial visit focused on elucidating the purpose of the interaction with the farmers. We invited them to participate in the experiment and survey during this visit. Upon receiving their consent, we arranged a mutually convenient time for an experiment. Following this, we visited each respondent’s residence to conduct the final experiment.

We provided an elaborate overview of the experimental procedure, followed by the live session. The experiment commenced with a practice session, allowing participants to seek further clarification. These preliminary sessions aimed to ensure participants' comprehensive understanding of the experimental protocol. When participants were prepared to proceed to the final session, we instructed them to complete the binary choices across all three series. Through random selection, each participant chose a single row from each choice set for payment allocation.

For instance, if a subject randomly selected row 10 can receive Rs. 400 or Rs. 100 with probabilities 30 percent and 70 percent respectively, if an individual chooses lottery A and Rs. 3000 and Rs. 50 with probabilities 10 percent and 90 percent, respectively if he/she opts lottery B. Similarly, in choice set two, if individual randomly chooses row 5 then prospect of winning the lotteries are Rs. 400 and Rs. 300 with probabilities 90 percent and 10 percent, respectively if he/she selected lottery A and Rs. 1060 and Rs. 50 with probabilities 70 percent and 30 percent, respectively, if he/she chooses lottery B. A similar process was also followed in choice set 3 where both lotteries have negative payoffs and equal probabilities in both games.

Upon completion of the experiment, participants were requested to fill out a survey concerning farm-related and farmers' characteristics. It is pertinent to highlight that the participants were predominantly farmers with relatively limited educational backgrounds. Given this context of an experiment, obtaining their consent for both the experiment and survey was important for the researchers.

4.6 Estimation of Parameters

We employed the TCN approach, encompassing 33 distinct scenarios for each individual, to estimate the parameters of PT. Within the context of the utility model mentioned above, the selection between two prospects within a game establishes the values for both risk aversion and probability weighting. These choice scenarios are distributed across three distinct segments. The initial two sets of choice scenarios elucidate risk aversion and probability weighting, respectively. The interplay between these elements is jointly derived from the choice sets within series one and two, which are utilized to measure risk aversion within the positive domain and nonlinear probability weighting.

Numerous methodologies have been developed to estimate these parameters within the framework of Prospect Theory utility functions[23]. In line with this, we adopted the approach that Tanaka et al. (2010) and Liu (2013) outlined. In this method, the model captures information related to the switching points across all experiment series. These switching points provide insights into the underlying risky behaviors. If an individual switches at row *n*, this signifies their preference for Lottery B over Lottery A at that specific row, and for Lottery A over Lottery B at row *n*- 1. Where n is the number of rows.

Guided by lottery choice scenarios, series one and two adhere to a defined set of inequalities at these switching points. Risk aversion (α) and probability weighting (γ) are determined concurrently. Consequently, we ascertain the range within which α and γ fall, satisfying these inequalities. Now, suppose an individual switch from lottery A to lottery B at row seven for series one and two. Utilizing the switching points from series one and two, the following inequalities must be upheld. This presupposes an individual switches from Lottery A to Lottery B at row seven for series one and two.

$$
\begin{aligned}
&100^{\alpha} + \exp[-(-\ln 0.3)^{\gamma}]\,(400^{\alpha} - 100^{\alpha}) > 50^{\alpha} + \exp[-(-\ln 0.1)^{\gamma}]\,(1250^{\alpha} - 50^{\alpha})\\
&100^{\alpha} + \exp[-(-\ln 0.3)^{\gamma}]\,(400^{\alpha} - 100^{\alpha}) < 50^{\alpha} + \exp[-(-\ln 0.1)^{\gamma}]\,(1500^{\alpha} - 50^{\alpha})\\
&300^{\alpha} + \exp[-(-\ln 0.9)^{\gamma}]\,(400^{\alpha} - 300^{\alpha}) > 50^{\alpha} + \exp[-(-\ln 0.7)^{\gamma}]\,(650^{\alpha} - 50^{\alpha})\\
&300^{\alpha} + \exp[-(-\ln 0.9)^{\gamma}]\,(400^{\alpha} - 300^{\alpha}) < 50^{\alpha} + \exp[-(-\ln 0.7)^{\gamma}]\,(680^{\alpha} - 50^{\alpha})
\end{aligned}
\tag{20}
$$

Given the stipulated inequalities, the parameters α and γ satisfying these conditions fall within the range of $0.26 < \alpha < 0.35$ and $0.66 < \gamma < 0.74$. Notably, the experiment was thoughtfully devised to ensure that the pair of switching rows within each experiment adhered to the upper and lower bounds of the parameters, in line with choices dictated by PT.

This study adopted the TCN method to ascertain the midpoints of these intervals with precision to two decimal points. Employing this approach, the estimated values for parameters α and γ were determined as 0.30 and 0.70, respectively. However, in instances involving extreme switching rows (i.e., switching at row one or abstaining from switching to Lottery B entirely), the TCN

[23] Abdellaoui (2000) and Abdellaou et al. (2007) developed a two-stage procedure to estimate these parameters.

method advocates for arbitrarily determining the parameter's lower or upper bound[24]. It is worth noting that such arbitrary determinations could potentially introduce noise into the data.
Following calculating the risk-aversion parameter α, a similar procedure involving inequalities was applied to the loss scenario parameter λ (series three). This entailed utilizing the switching point within series three. For example, for an individual who switches at row five in series three, the corresponding inequalities can be formulated as follows:

$$\exp[-(-\log 0.5)^{\gamma}](-\lambda)(-40)^{\alpha} + \exp[-(-\log(1-0.5)^{\gamma}(10)^{\alpha} > \exp[-(-\log 0.5)^{\gamma}](-\lambda)(-160)^{\alpha} + \exp[-(-\log(1-0.5)^{\gamma}(300)^{\alpha}$$

$$\exp[-(-\log 0.5)^{\gamma}](-\lambda)(-80)^{\alpha} + \exp[-(-\log(1-0.5)^{\gamma}(10)^{\alpha} < \exp[-(-\log 0.5)^{\gamma}](\lambda)(-160)^{\alpha} + \exp[-(-\log(1-0.5)^{\gamma}(300)^{\alpha} \quad (22)$$

Similarly to the above approximation of α and γ, we can identify the interval and use the midpoint of each interval as the point estimate value. We also used a similar procedure and found that the mean values of α, γ, and λ are 0.61, 0.65, and 3.02, respectively.

4.7 Data Collection and Sample Characterization

This study delves into the farmers' risk preferences within three villages located in Madhya Pradesh, one of India's agro-ecologically diverse states. This region has experienced remarkable growth, with an annual increase of approximately 10 percent for over a decade, garnering attention at the national level. The study reveals that this agricultural growth has been buoyed by various governmental supports, with a robust procurement system and the implementation of Minimum Support Prices (MSPs) as pivotal drivers of this success.

Madhya Pradesh (MP) boasts of a diversified crop production landscape, focusing significantly on food grains, including rice and wheat, alongside oilseeds and pulses. Notably, in Soybean production MP contributes around 60 percent of the country's total production. Additionally, there

[24] It is to explain, when switching rows take extreme values there is a possibility of potentially an infinite number of parameter combinations. In which, some of the switching rows are consistent if the possible value of ranges of parameters are unconstrained. If we assume $0< \alpha <1.5$ and $0< \gamma< 1$, then we can approximate parameter combinations for these as the mean of a truncated range of possible values for α and γ.

has been substantial growth in cultivating fruits and vegetables. Given the substantial potential for crop diversification, farmers' risk behavior is important in determining crop selection.

Government-led policy interventions, particularly the adoption of Minimum Support Prices (MSPs), stabilize prices and influence production decisions, specifically in crop selection. Consequently, a comprehensive analysis of the impact of MSPs on crop selection, while accounting for farmers' risk behavior, emerges as a vital consideration for the welfare of producers. Given the inherent variability in risk preferences and the availability of price stability, this study seeks to observe producer strategies to mitigate risk.

In this context, the study asked the following questions to the surveyed respondents:

- Do you prefer only non-MSP-backed crop items in your crop portfolio?
- Do you prefer both MSP and non-MSP-backed crop items in your crop portfolio?
- Do you prefer only MSP-backed crop items in your crop portfolio?

We selected three different villages in which farmers were, on average, producing various crops. First, we contacted the farmers to convince them and introduce the survey and experiment. 50 respondents from each village were included; out of 150 respondents, 16 were excluded due to invalid responses, making the final sample size 134 farmers for this study. We also tried to ensure that respondents must be the head of the family because they make all agricultural decisions. Conducting the experiment and survey took approximately 45 minutes for each respondent, and the actual payment mechanism was informed after the final experiment. The region has a diverse agricultural production, including various crops to choose from. This is worth mentioning as it allows farmers to choose the best crop in the production basket.

Based on the summary statistics presented in Table 4.2, the risk behavior of these farmers and farm characteristics play an important role. The average age of the farmers was approximately 48 years, with the study revealing a predominantly male presence among the decision-makers in agricultural production. Female representation in decision-making stood at a mere 3 percent. This highlights the limited participation of women in agricultural decision-making.

Table: 4.2 *Summary Statistics of Farmers and Farm Characteristics*

Farmers Characteristics			Mean/Percentage	Sd. Dev.
1.	Age	(years)	47.99	9.4
2.	Gender	(Male=1; Female=0)	94.78% Male	
3.	Education	(%)		
A.	No Edu		42.51%	
B.	School	(up to 12th)	48.53%	
C.	College		08.96%	
4.	Household Size	(nos.)	8.44	3.13
5.	People involved in agriculture (nos.)		3.15	1.83
6.	Annual household income	(Lakhs)	4.23	2.72
1 if	0 to 100000			
2 if	100001 to 200000			
3 if	200001 to 300000			
4 if	300001 to 400000			
5 if	400001 to 500000			
6 if	600001 to 700000			
7 if	700001 to 800000			
8 if	800001 to 900000			
9 if	900001 to 1000000			
10 if	1000001 to above			
7.	No of years involved in agri activities		23.01	11.29
8.	Farm Size (in acres)		3.20	3.95
9.	Total expected farm income	(Lakhs)	2.55	1.62
	(Similar definition as Annual Family Income)			
10.	No. of livestock	(nos.)	3.33	2.89

In terms of education, the survey indicated that around 22 percent of the respondents had received no formal schooling, 49 percent had acquired a primary school education, and 29 percent had pursued a college education. The average household size was 8.44, with an average of 3.11 family members actively involved in agricultural activities. The number of children within the household was reported as 3.46, while the annual household income averaged around 4.23 units. Finally, respondents possessed an average of 23 years of experience in agricultural activities.

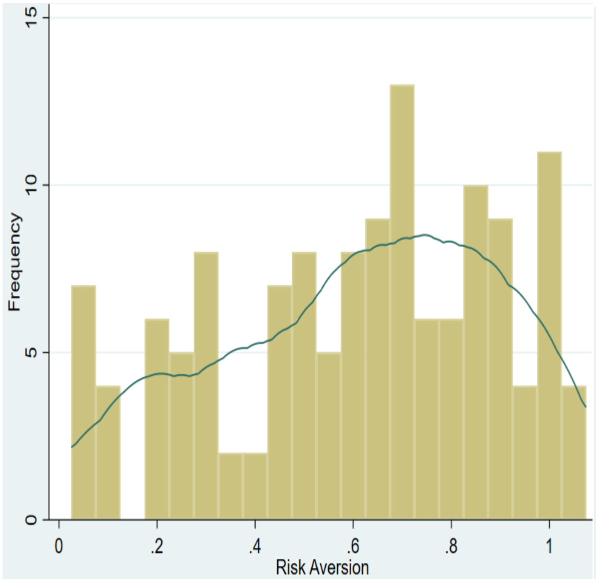
Detailing the farm characteristics, the average farm size was found to be 3.2 acres, with 0.46 acres allocated to land leased in and 0.34 acres for land leased out. Moreover, the average anticipated agricultural income per household was approximately 2.55, with a standard deviation of 1.62. As for livestock, each household reported an average of 3.33 livestock units. Regarding debts, 30.6 percent of the respondents acknowledged having debts from formal sources, while 19.4 percent reported debts from informal sources. About strategic decisions concerning crop selection for stable returns, only 20.15 percent of respondents indicated a strong inclination toward exclusively including Minimum Support Price (MSP) backed crop items in their production basket. Among the respondents, 45.52 percent reported a combination of MSP-backed and non-MSP items in their production portfolio. Additionally, approximately 34.33 percent of the respondents intended to opt for non-MSP crop items in their production basket.

4.8 Empirical Framework

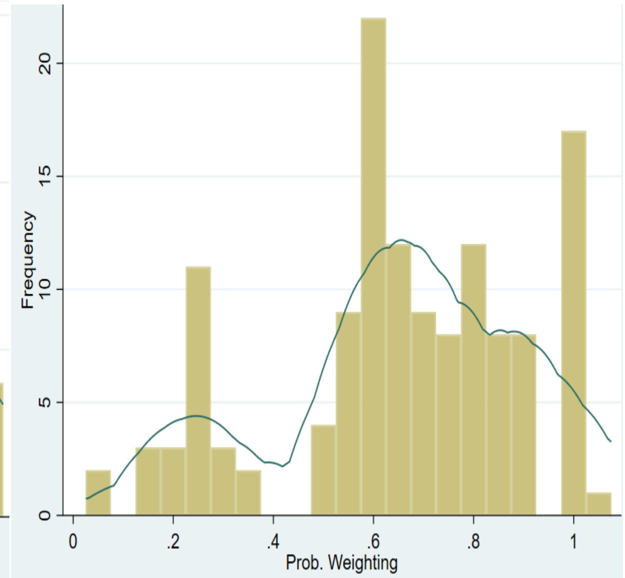
In this study, a Multinomial Probit Model (MPM) was employed to investigate the influence of risk preferences on the choices related to Minimum Support Price (MSP) in production decisions. Within the framework of the prospect theory model, the parameters—namely risk aversion, probability distortion, and loss aversion—contribute to explaining individual risk preferences. This model posits that the preference for selecting MSP-backed crops in production decisions is contingent upon risk preferences, encompassing risk aversion, probability weighting, and loss aversion. The model incorporates individual-specific control variables and elicits risk parameters represented as follows:

$$Yi^* = Xi'\beta_i + Zi'\gamma_i + ui \text{ for } i = 1, 2, \ldots, n \text{ where } ui \sim N(0, 1) \tag{23}$$

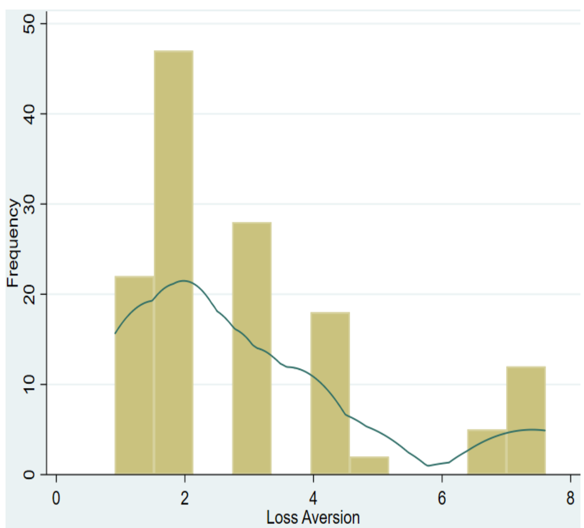
Here, Yi^* denotes the categorical variable about participants, where i varies from 1 to n, with n representing the number of participants. The categorical variables MSP1, MSP2, and MSP3 encompass potential options in production decisions to mitigate price risk through the Minimum Support Price policy. This study emphasizes the role of price stability as a crucial instrument for risk mitigation. This perspective is notably endorsed by the sensitivity of Indian farmers to price stability, as evidenced by recent movements advocating for the reinforcement of the MSP law.



(a)



(b)



(c)

Figure 4.1: *Distribution of PT Parameters*

We classified the level of risk preferences into four groups: high risk-averse behavior (range less than 0.33), moderate risk-averse behavior (ranging from 0.34 to 0.66), low risk-averse behavior (ranging from 0.67 to 0.99), and finally, risk neutral. Twelve respondents exhibited risk-neutral behavior (precisely equal to 1), serving as the reference point[25]. The ascending numerical order indicates decreasing levels of risk aversion. Similarly, we categorized loss aversion behavior into four tiers (risk-neutral, low loss aversion, moderate loss aversion, and high loss aversion). Among these, 17 respondents displayed loss-neutral behavior, serving as the baseline index with a value of 0[26]. Loss aversion parameters ranging from 1.1 to 2.5 were classified as low loss aversion, 2.51 to 4 as moderate, and above 4 as high loss aversion behavior. Higher numerical values signify greater levels of loss aversion behavior.

Finally, probability weighting was divided into four categories (neutral, low, moderate, and extreme moderate probability distortion behavior). The base category featured a probability weighting of 1. Seventeen respondents exhibited a probability weighting of 1 as the reference index. Probability distortion values ranged from 0.99 to 0.67 for low probability distortion, from 0.66 to 0.34 for moderate, and below 0.34 for extreme probability distortion behavior. Increasing numerical values denote a more significant distortion of stated probabilities in favor of lower probabilities.

4.9 Results

4.9.1 Risk Parameters Estimates

We adopted a similar experimental procedure as Tanaka et al. (2010) employed to estimate prospect theory parameters. The estimated mean risk curvature value is 0.61, indicating that the average farmers exhibit risk aversion. This value closely aligns with findings from a study involving Vietnamese farmers (0.66) (Liu & Huang, 2013). Similarly, in another study, Liu (2010) reported a mean risk curvature value of 0.48 among Chinese farmers. A comparative analysis of farmers in developed and developing countries suggests that farmers in the latter exhibit comparatively lower levels of risk aversion.

[25] We estimated 3 respondents elicited small risk-loving (1.05), we included in the base index due to very small risk loving indication.

[26] We found 5 farmers were reflected small loss loss-loving (0.91) therefore we included it into the base index.

Regarding loss aversion behavior, the average value observed in this study is 3.02, indicating that farmers are more responsive to losses than gains. This result implies that Indian farmers exhibit higher loss aversion behavior than Vietnamese farmers (2.63) and less loss aversion behavior than their Chinese counterparts (3.47)[27].

The average probability weighting observed in this study is 0.65, suggesting that, on average, farmers tend to assign greater weight to low probabilities and lesser weight to high probabilities. This value closely approximates the mean values estimated for Vietnamese (0.74) and Chinese farmers (0.69).

We illustrate the simulated PT values from the equation shown in Figure 4.1(a). The function demonstrates the risk and loss behavior of an average farmer. As anticipated, the curvature of the PT value function in both the gain and loss domains aligns with the fundamental prospect theory principles; the PT utility is concave in the gain domain and convex in the loss domain. The figure also indicates that the slope of the value function is steeper in the loss domain compared to the gain domain.

In Figure 4.1(b), we depict the PT weighting function using the mean value of the estimated parameter γ. The figure reveals that farmers tend to overestimate probabilities by approximately 0.60, and this overestimation becomes more pronounced as the probability approaches zero. This observation suggests that farmers distort extreme probability values, specifically 0 and 1. The mean value of the estimated probability weighting was found to be 0.65.

Next, we examine these risk parameters within different groups of farmers categorized by their land-holding patterns, as presented in Table 4.3. The findings indicate that small-scale farmers exhibit less risk aversion behavior and less probability weighting distortion than large-scale farmers. Conversely, the results suggest large-scale farmers are more loss-averse, while median-scale farmers demonstrate significant probability distortion.

[27] Some studies in developed world witnesses, Bocquého et al. (2014) and Piet and Bougherara (2016) both conducted their experimental study on French farmers and Zhao & Yue (2020) USA farmers. Bocqueho et al. (2014) and Piet and Bougherara (2016) estimated risk curvature, loss aversion and probability weighting respectively, (0.28, 2.28, 0.66) and (0.62, 1.39, 0.82), where Zhao & Yue (2020) estimated parameters are (0.327, 1.596, 0.696).

Furthermore, to observe the parameter variability based on respondents' preferences for MSP in crop selection, we present the outcomes in Table 4.4. The results reveal that farmers who exclusively opt for MSP-backed crop items manifest significant risk aversion, loss aversion, and substantial probability distortion compared to other groups. This reveals the pivotal role of farmers' risk behavior in influencing crop selection, particularly in favor of including MSP-backed items within the production portfolio.

Table: 4.3 *Mean Value of Estimated Risk Parameters (Based on Land Holding)*

Land Holding Size	Risk aversion	Loss aversion	Prob. Weighting
More than 5acres	0.56	3.49	0.63
5 acres to 2 acres	0.58	2.58	0.51
Less than 2 acres	0.65	2.78	0.73
Total	0.61	3.02	0.65

Table: 4.4 *Mean Value of Estimated Risk Parameters (Based on MSP Choices)*

MSP Categories	Risk aversion	Loss aversion	Prob. Weighting
MSP1	0.69	2.57	0.72
MSP2	0.64	2.92	0.70
MSP3	0.41	3.98	0.44

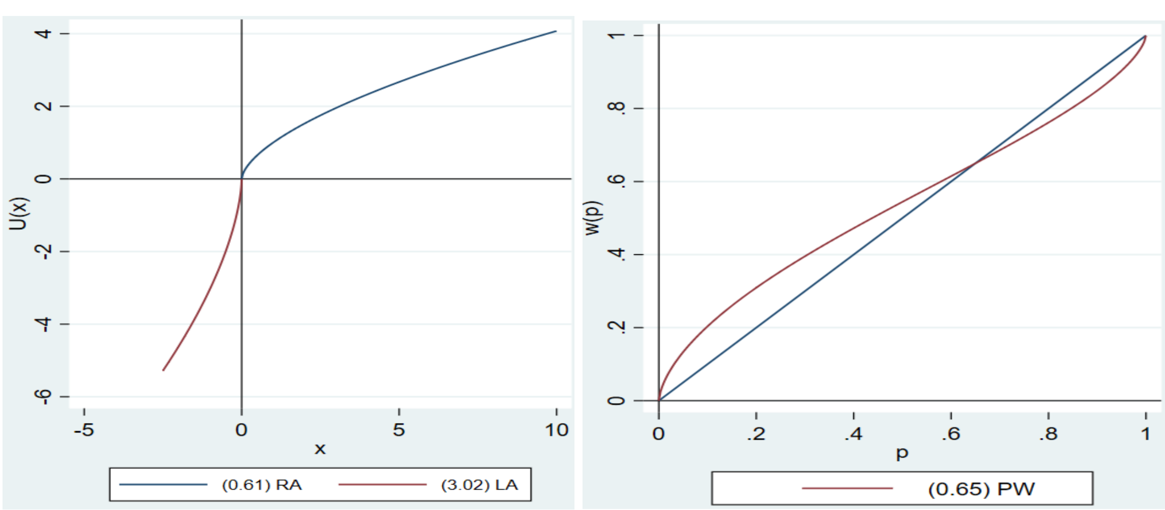


Figure: 4.2 *CPT value function and weighting Function Curve*

Table: 4.5 *Determinants of MSP Crops Adoption among Farmers*

Variables	MSP2		MSP3	
Low-Risk Aversion	0.201	(0.864)	-2.322	(2.179)
Moderate Risk Aversion	0.837	(0.863)	0.636	(1.501)
High-Risk Aversion	2.451**	(1.265)	3.060**	(1.794)
Low Prob. Distortion	-0.940	(0.948)	0.371	(2.037)
Moderate Prob. Distortion	-1.018	(0.977)	1.783	(2.042)
High Prob. Distortion	-2.616***	(1.385)	1.022	(2.193)
Low Loss Aversion	1.614***	(0.755)	3.406***	(1.846)
Moderate Loss Aversion	0.173	(0.801)	2.810**	(1.968)
High Loss Aversion	0.539	(0.812)	3.215***	(1.817)
School Education	-0.201	(0.526)	1.275	(0.872)
College Education	1.905	(2.087)	3.978***	(2.361)
Farm Land (acreage)	1.062***	(0.266)	1.335***	(0.287)
Age	-0.225	(0.315)	0.904**	(0.517)
Number of people in family	0.122	(0.113)	0.329**	(0.175)
Household Income	0.182	(0.148)	0.299*	(0.192)
No of years involved in agri activities	-0.057	(0.308)	-0.158	(0.472)
Livestock	-0.558***	(0.139)	-1.044***	(0.258)
Constant	-0.472	(1.939)	-15.056***	(4.885)
Observations	134		134	

Standard errors in parentheses

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

4.9.2 Risk Behavior and MSP Crop Decisions

Table 4.5 reports the result of the Multinomial Probit Model (MPM) of the main effect. The table consists of the MSP2 and MSP3; the MSP1 group is considered a reference group in the model. The result describes the relationship between farmers who adopt MSP crop items and explanatory variables with a reference group of farmers who do not prefer MSP crops. The result shows that the group of farmers who adopt only MSP crop items (MSP3) is statistically significant concerning high-risk and across the loss-aversion. It indicates that farmers who are either less loss-averse, moderately loss-averse, or highly loss-averse are positively related to MSP preferences.

This can be interpreted as, for example, a unit increase in the loss-aversion parameter in the group of MSP3 farmers; either farmers are less loss-averse, moderately loss-averse, or highly loss-averse, they are three times more sensitive to adopting MSP crop items than a group of farmers who do not adopt MSP crop (MSP1). The result also indicates that high-risk aversion is equally sensitive to aversion in the MSP3 group.

The results indicate significant differences when comparing the MSP2 group of farmers with the reference group MSP1. Specifically, the MSP2 group exhibits less loss aversion, higher risk aversion, and higher probability distortion. Furthermore, the adoption sensitivity of MSP items within this group is notably reduced.

Moreover, the findings demonstrate that a higher probability distortion is inversely correlated with adopting MSP-backed crop items. In other words, farmers' likelihood of incorporating MSP items into their production diminishes as they engage in probability weighting distortion.

This finding suggests that adopting MSP crop items in production decisions cannot be solely attributed to risk aversion behavior. As anticipated, farmers exhibit a heightened sensitivity to losses, surpassing their risk aversion tendencies. Consequently, their inclination towards preferring MSP crops in production becomes more pronounced. Therefore, a robust relationship between loss aversion and MSP adoption is evident.

Further, farmers exhibiting high probability weighting distortion are statistically significant and negatively related to the MSP2 groups. Wu and Gonzalez (1996) pointed out decision-maker sensitivity to changes in probability. Interestingly, the results demonstrate that a high level of probability weighting distortion does not significantly contribute to the adoption of MSP crop items compared to loss aversion behavior. This discrepancy in behavior is inconsistent within the context of MSP adoption. A farmer might find gambling attractive, indicating a preference for risk-seeking behavior. However, the same farmer concurrently prefers MSP crop items to mitigate price risk.

The results clarify the significance of the critical determinants of risk attitudes, particularly loss behavior, in comprehending risky agricultural decisions. This observation can be interpreted in the context of the high volatility of agricultural prices in Indian agriculture. Farmers often encounter substantial losses when prices sharply decline, especially in non-MSP crop items. Such events are common, particularly in crops like onions and potatoes, where prices can plummet drastically, leading to significant financial losses for farmers.

Concerning the influence of farms and farmers' characteristics on agricultural decision-making, our findings highlight the significance of education, which is statistically significant and positively correlated with the adoption of MSP crop items. Farmers with higher levels of education are more inclined to choose MSP crop items in their production decisions.

We found that certain variables, such as farmers' lack of education and the number of family members involved in agricultural activities, are not statistically significant in the model. This could be attributed to previous studies emphasizing the notable link between risk attitude and education (cognitive ability) in decision-making. In recent literature, cognitive factors have been connected to learning capacity, adoption of sustainable practices, and a better grasp of cost-benefit analyses. These factors contribute to farmers' precision in decision-making (Dessart et al., 2019). Dohmen et al. (2010) suggest that lower cognitive ability is associated with higher risk aversion and greater impatience, significantly impacting decision-making processes[28].

Regarding farm characteristics, we observed that farm size holds statistical significance and indicates a greater preference for MSP crop items as the farm size expands. This aligns with the notion that larger farmers have experienced more advantages from the MSP policy, potentially rendering them more inclined towards adopting risk-mitigating strategies. Furthermore, our findings highlight that the presence of livestock is also statistically significant in influencing MSP responses. Specifically, we determined that farmers' inclination towards MSP preference exhibits a negative correlation with the presence of livestock.

[28] Andersson et al. (2016) interpreted that cognitive ability is linked to random decision-making rather less risk preference behavior.

4.10 Discussion

The field of agricultural economics has extensively delved into the empirical models governing risk management decisions. Willock et al. (1999) emphasized the pivotal role of attitudes and strategies in shaping farming practices [29]. They contended that these variables serve as intermediaries between dependent variables and intervene as mediating factors within the decision-making process. For instance, a farmer's attitude mediates general agricultural practices and specific farm objectives. This implies that farmers employ a variety of strategies to mitigate risk in their production decisions, wherein crop selection and diversification have remained traditional methods. However, gaining a comprehensive understanding of the institutional support of agricultural risk management necessitates a grasp of farmers' risk attitudes and corresponding responses to policy initiatives.

Minimum Support Price (MSP) represents a significant policy initiative for Indian farmers. The recent farmer protests against new farm laws have thrust the issue of MSP into the spotlight (Gupta et al., 2021). Criticisms directed towards MSP revolve around limited awareness and minimal beneficiaries. An assessment of agricultural households conducted by the National Sample Survey Office (NSSO) reported that merely 6 percent of farmers were aware of MSP and engaged in selling their produce to the government across India during the 70th round (2012-13). The report further underscored substantial disparities among states selling rice and wheat at MSP. For example, while Chhattisgarh accounted for 38 percent of rice, Punjab and Haryana accounted for 62 and 39 percent of wheat sold at MSP, respectively. Nevertheless, the potential impact of MSP on influencing farmers' production decision-making remains relatively unexplored. In scenarios where risk mitigation strategies are limited, farmers often wield MSP as an efficacious tool when making crop choices within the realm of production decisions.

This study focuses on farmers' risk attitudes and their pivotal role in responding to Minimum Support Price (MSP) within production decisions. We employed the experimental method of lottery choice gambling to measure risk attitudes effectively. The results gleaned from this approach have underscored theoretical and empirical dimensions and emphasized the pronounced

[29] A group of experts from different field is also called Edinburgh study on farm decision making comprises multidisciplinary researchers, i.e., rural resource management, business management, mathematical and statistical modeling came into conclusion that attitude in the farm decision is a distinct variable.

significance of loss-aversion behavior over risk-aversion behavior. This loss-aversion behavior is the primary determinant in comprehending farmers' reactions to risk mitigation strategies. Notably, an escalated inclination towards loss-aversion behavior exhibits a positive correlation with the propensity to adopt more MSP items as strategies for risk management.

This study contributes significantly to the existing literature by employing prospect theory to unravel risk behavior and establishing a tangible link between such behavior and tangible decisions, all within the context of MSP. In doing so, it augments the range of available models, moving beyond the confines of expected utility theory and providing a fresh perspective to the discourse.

This study also highlighted the imperative need to treat loss behavior and probability weighting as distinct and separate phenomena, equally deserving of individual emphasis alongside risk aversion within the analysis behavior analysis, which is deemed equally pivotal and capable of autonomous influence in comprehending farmers' choices concerning risk management. Recognizing loss aversion behavior and probability weighting as independent drivers in understanding farmers' risk management decisions is crucial. Notably, the observed consistency of loss aversion behavior with findings from other studies is noteworthy. For instance, Liu & Huang (2013) established the statistical significance of loss aversion concerning mean village income. Meanwhile, Liu (2012) deduced the significance of loss aversion in shaping the adoption of new technology among Chinese farmers.

In this context, the experimental method plays a pivotal role in capturing the extent of risk attitudes. Using experimental methods to gauge risk attitude in agricultural decisions remains relatively uncommon. Nevertheless, several studies have delved into the role of parameters like risk aversion, loss aversion, and probability distortion within diverse agricultural decision-making contexts by employing such experimental techniques in conjunction with prospect theory (Liu 2012; Liu & Huang 2013; Zhao & Yue 2020; Villacis et al. 2021; Bougherara et al. 2017; Bocquého et al. 2014).

Finally, this study underscores the significance of loss-aversion behavior within the context of risk-mitigation strategies among Indian farmers. As Kahneman and Tversky (1984) posited, loss aversion materializes when the prospect of losses carries more weight than equally valued gains.

This phenomenon resonates in Indian agriculture, where market price volatility and potential losses exert a more substantial influence on farmers' decisions, prompting them to opt for more stable items in their production choices. This could potentially contribute to the fervent protests witnessed against new farm laws. An essential policy implication derived from this study also pertains to Indian agriculture's trajectory, demonstrating an inclination toward producing a significant volume of wheat and rice—more so than what policymakers might have initially anticipated as a response to MSP in production decisions.

4.11 Conclusion

MSP is the current issue in Indian agriculture discourse. A recent farmer’s protest against new farm law and in favor MSP thrives to discuss it by government agencies, agricultural economists and policy-makers. This study find that MSP is a significant factor in the farm production decisions. MSP serve its purpose to reduce income risk which has been the primary objective of this policy. Farmers also responding accordingly as reducing the losses in the production. We find that loss aversion behavior is a significant factor in explaining the MSP adoption strategy.

Chapter 5

Role of Risk and Uncertainty in Seed Adoption: A Cumulative Prospect Theory Approach

5.1 Introduction

In the literature concerning agricultural risk behavior, the risk aversion behavior of farmers in decision-making is of much importance. Numerous studies have simulated risk scenarios to observe farmers' behavior and understand the impact of risk and risk aversion on agricultural decision-making. Several studies have also investigated the effects of risk on technology adoption within various contexts (Atanu et al., 1994; Adesina & Zinnah, 1993; Ross et al., 2012; Abebe et al., 2013; Liu, 2012). More recently, researchers have directed their attention toward examining the effects of uncertainty on technology adoption (Barham et al., 2014; Chavas & Nauges, 2020; Engle Warnick et al., 2011; Marra et al., 2003; Ross et al., 2012). It can also be argued that the uncertainty phenomenon is more closely aligned with real-world situations.

Recent technological advancements in improving seed varieties have played a crucial role in enhancing agricultural productivity, addressing climate-related concerns, and improving farmers' livelihoods. Over the past two decades, significant progress has been made in developing improved seed varieties. However, there remains to be a certain degree of hesitancy, particularly among smallholder farmers in the developing world, when adopting these advancements. Despite such investments' readily available, cost-effectiveness, and profitability, the adoption and demand for improved seed varieties often fall short of expectations (Spielman & Smale, 2017; Hoogendoorn et al., 2018).

Previous studies on farmers' adoption of new seed varieties in diverse contexts have contributed to our comprehension of the subject. For instance, improved seed varieties are designed and introduced to align with the needs and demands of farmers. Nonetheless, recent studies highlighted limitations in the underlying research methodology. Neglecting the uncertainty within the model has led to an overemphasis on the significance of risk-related phenomena (Engle Warnick et al., 2011; Ross et al., 2012b). Given the mixed experiences encountered, there is a need to comprehend the potential influence of both risk and uncertainty on the demand for new seed varieties. This study approaches the behavioral model from the perspective of subjective disparities rooted in heterogeneous perceptions of risk and uncertainty in decision-making.

In much of the research, farmers' preferences for seed adoption are examined using experimental methods, wherein farmers are prompted to bid for or purchase seed bags in both hypothetical and real-life scenarios. These designed experimental methods often need to pay much attention to the real-world decision context. Further, several other methods employed in previous studies explore the social and personal contexts of decisions while often disregarding external factors that also play a crucial role in technology adoption.

Adopting a new seed variety is not a one-time event; it requires continuous adoption and adaptation in each subsequent season to achieve optimal production. This holds for all hybrid seeds, which can be planted only once since seeds obtained from such crop output yields low productivity. A case in point is the observation that farmers in Madhya Pradesh tend to reuse seeds persistently, resulting in low seed replacement rate (SRR). As of 2011 data, Madhya Pradesh exhibited an SRR of merely 16 percent in paddy production, in stark contrast to Andhra Pradesh, which topped the list with an SRR of 87% (Ministry of Agriculture GoI report, 2011).

This study aims to analyze the behavior of risk and uncertainty among small Indian farmers and its impact on adopting new seed varieties in paddy production. This analysis encompasses adopting new seed varieties within the present production season and over the preceding three years. Employing an experimental approach, this study generates an environment characterized by risk and uncertainty, subsequently investigating the adoption patterns of actual seed varieties during the paddy season of 2021-22 in Madhya Pradesh and analyzing its outcomes.

The remainder of the chapter is structured as follows: Section 5.2 provides an overview of past studies on farmers' risk behavior, followed by the theoretical model and experimental methodology for eliciting risk and uncertainty behavior in section 5.3. This study employs the Holt-Laury experimental procedure to comprehend behavior under these conditions. Section 5.4 outlines the econometric method used in this study, while data collection and the experimental setup are detailed in section 5.5. The main empirical findings of the paper are presented in section 5.6, followed by subsequent discussions and conclusions in sections 5.7 and 5.8, respectively.

5.2 Literature Review

A substantial body of literature has extensively investigated adopting diverse technologies in agricultural production. These studies have primarily focused on decision variables within production, input constraints, and productivity. In a comprehensive examination of technology adoption, Magruder (2018) underscored that credit and insurance are the most pivotal limitations for technology adoption in developing nations. The sluggish response to adopting new technology following various policy initiatives is attributed to an information gap. Consequently, disseminating information regarding policy initiatives assumes critical significance in the adoption of new seeds in the decision-making process. This study also emphasized the significance of production risk, which shapes credit and input considerations within the production decision. Variations in technology adoption of this nature may, in turn, influence individual behavior, particularly the attitudes toward risk and uncertainty of decision-makers. Some studies have observed the role of individual perceptions and attitudes toward technology adoption (Yamano et al., 2015; Atanu et al., 1994; Adesina & Zinnah, 1993).

The adoption of innovation is an aspect of the broader decision-making process. It involves incorporating new knowledge and resources into production, driven by the anticipation of benefits. However, evaluating the perceived benefits of technological changes is rarely straightforward; inherent in such evaluations are potential risks and uncertainties.

The empirical literature on risk and uncertainty and their association with individual characteristics and well-being is essential (Cardenas & Carpenter, 2013) in economic development. The role of risk and uncertainty behavior (Bouchouicha & Vieider, (2019) drive innovation and related decisions have a crucial role.

Marra et al. (2003) delineated the adoption process of novel technology within environments characterized by risk or uncertainty. Their work highlighted the significance of learning and information dissemination within the agricultural sector. They concluded that farmers' risk perception and attitudes are pivotal to technology adoption. Similarly, Meraner & Finger (2019) and van Winsen et al. (2016) delved into the determinants of risk behavior and risk management strategies among farmers using survey data. These studies identified the contextual factors and individual risk perceptions as pivotal indicators influencing decision-making.

Studies have consistently highlighted that farmers' perceptions of adopting new technology are heavily influenced by socioeconomic determinants, including their social standing, the crop variety within their farming system, prevailing agro-ecological conditions, market connections, and more (Yamano et al., 2015). Furthermore, the context exhibits a high degree of variability tailored to the specific requirements of each region. Given this departure from established technologies, adopting new technologies introduces additional uncertainty and uncertainty (Engle Warnick et al., 2011; Liu, 2012; Lybbert & Bell, 2010). This notion is widely acknowledged in the literature on technology adoption (Foster & Rosenzweig, 2010). In seed adoption among subsistence farmers, adopting new seeds is linked to risk aversion and uncertainty aversion, making them less inclined to favor new varieties. Recent studies have identified uncertainty aversion as a significant obstacle to technology adoption (Engle Warnick et al., 2011; Engle-Warnick et al., 2007; Ross et al., 2012b). However, understanding the potential interplay of risk and uncertainty in the decision-making process concerning major crops among small farmers remains a critical research gap. This study aims to enrich our comprehension of agricultural technology adoption and the extent to which farmers are at risk and uncertainty when making decisions. Additionally, this study observes the influence of credit constraints from formal sources, which curtail the responsiveness to technology adoption.

Farmers with a higher risk aversion tend to show reduced demand for new crops to diversify their seed portfolio. This phenomenon arises because, during the decision-making process for production, the available new crop varieties lack sufficient information regarding the probable outcomes. The expansion of technology adoption depends on the technological characteristics required in specific regions and individual attitudes toward risk and uncertainty. Consequently, incorporating heterogeneity at the individual level is imperative to model the new technology adoption trends.

The scenario of uncertainty materializes when farmers possess comparatively limited information about new seed varieties compared to the familiar seed crops used in the past. If farmers opt for familiar crops and disregard new seed varieties, it suggests that risk aversion adequately explains their approach to new seed adoption. However, if farmers frequently opt for new crop varieties in their production decisions, their behavior might be better understood through uncertainty aversion. Since farmers have empirically observed biased behavior in yield responses to inputs, assessing whether these behavioral factors, such as biases, also manifest in crop selection becomes crucial.

Most previous studies that analyzed risk behavior based on expected utility have faced substantial criticism from Tanaka, Camerer & Nguyen (2010) and Liebenehm & Waibel (2014). These researchers advocated prospect theory as a more suitable model for examining risk behavior. They argued that prospect theory provides a superior framework for understanding risk behavior. An influential work by Kahneman & Tversky (1979) delved into the choice problem under risk and demonstrated that individual risk preferences systematically deviate from conventional expected utility theory predictions. This pioneering study introduced the concept of PT wherein three distinct parameters were proposed to elucidate risky behavior: the value function, loss aversion, and probability weighting. The value function parameter accounts for changes in wealth or utility rather than just the final wealth in an investment. The loss aversion parameter posits that decision-makers exhibit heightened sensitivity to losses compared to gains. Consequently, gains and losses are not perfect substitutes, as the expected utility model suggests. The third parameter, probability weighting, indicates that decision-makers over-emphasize small probabilities and under-emphasize large probabilities. Behavioral economists use these parameters to explain deviations in risky behavior.

In this current study, we leverage these three parameters that govern risky behavior, alongside uncertainty aversion, to examine the influence of farmers' risk behavior on adopting new seeds in rural India. In this context, uncertainty aversion behavior pertains to changes in individual risky behavior caused by an information gap in probabilities.

5.3 Theoretical Model

5.3.1 Model of Risk Aversion Measurement

An alternative theory of risk behavior, namely CPT proposed by Tversky & Kahneman (1992), became a popular method of analyzing risk behavior. In order to describe the CPT, includes three important parameters to capture the risk characteristics of individual behavior. The first parameter is risk curvature (α), which describes the prospect value function. It is also a proxy of the risk aversion parameter. The second parameter is loss aversion (λ), which characterizes the individual behavior in a loss domain, and the third parameter is probability distortion (γ), which describes individuals' probability-distorting behavior in the given probabilities. Now, consider the risky prospects with two possible outcomes, y_1 and y_2, occurring of respective probabilities *p* and *q*, (*p* + *q*=1). To define the utility function under CPT, a value of prospect is:

$$\mathrm{U}(y_{1,}\, y_2, p, q) = \begin{cases} u(y_2)\, w(p) + \ w(p)[\ (u(y_1) - \ u(y_2)]; & if\ y_1 \geq \ y_2 \geq \ 0 \\ & or\ \ y_1 \leq \ y_2 \leq \ 0 \\ \ w(p)u(y_1) + \ w\ (q)\, u(y_2); & if\ y_1 < 0 < y_2 \end{cases} \qquad (5.1)$$

where utility is the expected value over binary prospects y_1 and y_2 with corresponding probabilities *p* and *q*. The individual preference is represented by a function that assigns different values for gains ($y > 0$) and losses ($y < 0$), as follow:

$$u(y)\ = \begin{cases} y^{\alpha} & if\ y \geq \ 0 \\ -\ \lambda\, (-y^{\alpha}) & if\ y < 0 \end{cases} \qquad (5.2)$$

Next, the probability weighting function in equation (5.3) is axiomatically derived by Prelec (1998). It is one of the popular methods and flexible enough to include decisions consistent with expected utility theory.

$$w(p) = \exp\,[-(-\ln p)^{\gamma}\ ] \qquad (5.3)$$

where, γ is the probability weighting parameter, which reflects that agent overestimates a small probability and underestimates a large probability if γ < 1. This can be interpreted as if 1 = λ = γ, then prospect theory is reduced to the expected utility theory.

Next, to measure the loss aversion parameter λ, the experiment is designed in the payoff matrix in experiment three, assuming that the individual switches from option A, certain payoff to lottery B in round i. This experiment consists of positive and negative payoffs in both lottery experiments, options A and B. Given the experimental procedure, it is assumed that the utility derived from option A in round i is similar to that derived from lottery B in round i. Therefore, the loss aversion parameter λ_i is consistent at the switching point and is a function of risk aversion α, and there is a range of values for λ_i for a particular value of α. Therefore, in order to estimate the range of value of λ_i for a particular α, and to estimate the upper bound of $\lambda_i(\alpha)$, it is

$$\lambda_i(\alpha) = \frac{y_{1A,i}^{\alpha} - y_{1B,i}^{\alpha}}{\left(-y_{2A_i}\right)^{\alpha} - \left(-y_{2B_i}\right)^{\alpha}} \tag{5.4}$$

where $y_{1A,i}$ and $y_{1B,i}$ are the choice of positive payoffs in round i, and $y_{2A,i}$, and $y_{2B,i}$ are corresponding choices of negative payoffs, corresponding to these lottery options A and B, respectively.

5.3.2 Experimental Procedure of Risk Aversion Measurement

Measurement of risk aversion in the game, i.e., the experimental instrument, is presented in payoff matrix experiment one. It consists of a similar 12 binary preferences between sure and risky options in the game. In the experiment, the left side is presented with a certainty payoff of Rs. 100, whereas the right side is a risky option. The first round consists of a 0.10 probability of getting Rs. 260 and a 0.90 probability of getting Rs. 50. Further, in round two, the probability of 0.10 with associated payoffs monotonically increases up to Rs. 1330 to round 12, and other payoffs remain constant.

To measure the risk aversion α and probability weighting γ, we developed an experiment characterized by prospect valuation. An individual prefers to choose the prospects y_1 and y_2 in each experiment against the corresponding risk-free option. The payoff matrix table 5.1 and table 5.2 present the 12 choice options, scenarios of two different risky prospects against specific outcomes; choices are made between a risk-free option (certain A) and a risky option (lottery B). The individual response of lotteries in both these tables captures the risk aversion and probability weighting, where these two parameters are simultaneously determined.

Table: 5.1 *Payoff Matrix Experiment One*

	Fixed	Risky	
		Black	**Red**
		(0.10%)	**(0.90%)**
1.	100	260	50
2.	100	280	50
3.	100	320	50
4.	100	360	50
5.	100	410	50
6.	100	470	50
7.	100	560	50
8.	100	630	50
9.	100	720	50
10.	100	850	50
11.	100	1040	50
12.	100	1330	50

Table: 5.2 *Payoff Matrix Experiment Two*

	Fixed	Risk	
		Black	**Red**
		(0.70%)	**(0.30%)**
1.	400	560	50
2.	400	570	50
3.	400	600	50
4.	400	620	50
5.	400	650	50
6.	400	690	50
7.	400	730	50
8.	400	770	50
9.	400	820	50
10.	400	870	50
11.	400	950	50
12.	400	1050	50

The experiment is designed so that fixed and risky payoffs are constant for every round in the risky choice, except only winning payoffs in the random draw monotonically increase over each row. Therefore, experimental design makes it easy for the respondents' utility payoffs and switch their preferences. Respondents can switch the options only once among all 12 rounds of each experiment to enforce the choice consistency with monotonicity in preferences. This is a similar procedure as Tanaka et al. (2010) and Liu (2013) elucidated that capturing the information through switching by an option in the rounds is sufficient to identify the underlying behavioral parameters. A switching point in each experiment is consistent with the utility function and range of possible values for α and γ.

Based on these experiments, respondents can switch to any row, and it is concluded that they prefer certain option A over Lottery option B in this particular row. Suppose that the respondent switches at row 5 in payoff matrix table 5.1 and at row 6 in payoff matrix in table 5.2 from risk-free option (option A) to risky option (option B); then the following inequalities should be satisfied:

$$
\begin{aligned}
&100^{\alpha} > 50^{\alpha} + \exp\left[-(-\ln 0.1)^{\gamma}\right] (360^{\alpha} - 50^{\alpha}) \\
&100^{\alpha} < 50^{\alpha} + \exp\left[-(-\ln 0.1)^{\gamma}\right] (410^{\alpha} - 50^{\alpha}) \\
&400^{\alpha} > 50^{\alpha} + \exp\left[-(-\ln 0.7)^{\gamma}\right] (650^{\alpha} - 50^{\alpha}) \\
&400^{\alpha} < 50^{\alpha} + \exp\left[-(-\ln 0.7)^{\gamma}\right] (690^{\alpha} - 50^{\alpha})
\end{aligned} \tag{5.5}
$$

Given these sets of inequalities, we can identify the ranges of both parameters α and γ that satisfy these inequalities. If respondents never switch or switch at the very first row, then we have one inequality for each experiment. For each parameter satisfying the above inequalities (range of values), we accounted for the midpoint of each interval up to two decimal points. After getting this parameter α and γ in the given equation, we can calculate the loss aversion parameter using equation 5.4 and experiment with payoffs in table 5.3.

Finally, in the loss aversion experiment parameter λ measurement, respondents were presented with seven round choice option scenarios, comprising both options as risky choices. The experimental design comprised positive payoffs of drawing a winning lottery and negative payoffs of losing the lottery draws. The payoffs in each round vary, and payoffs were specified to capture respondents' loss aversion behavior in the range of possible parameters.

Table: 5.3 *Payoff Matrix of Experiment Three*

	Risk option A		Risk option B	
	Black (0.50%)	**Red (0.50%)**	**Black (0.50%)**	**Red (0.50%)**
1.	250	- 40	300	- 210
2.	40	- 40	300	- 210
3.	10	- 40	300	- 210
4.	10	- 40	300	- 160
5.	10	- 80	300	- 160
6.	10	- 80	300	- 140
7.	10	- 80	300	- 110

5.3.3 Model of Uncertainty Measurement

Uncertainty is an inability to formulate expectations about possible outcomes, and it arises due to a lack of information. For instance, a new technology adoption inhibits decisions due to the need to formulate the prospects among options. Thus, uncertainty aversion is defined as a discount factor of incomplete information that reduces the perceived value of a prospect. As an early exposition of Three-Colour, Ellsberg Paradox (1961) provides an incentive for two thought-experiment decision problems, in which he describes the preference for known payoffs over the ambiguous event, known as uncertainty aversion. More recently, Klibanoff et al. (2005) described a two-stage model of uncertainty behavior: in the first stage, the individual exhibited the same risk attitude and derived uniform utility for all prospects, whereas, in the second stage, a new utility function, a representation of second ordered utility function was defined over first ordered probability. This function is similar to the vNM utility function over risky prospects.

Measuring the uncertainty behavior, it is considered that utility is assumed to be derived from associated options (risk and uncertainty) in a given series of risk and uncertain events. In capturing uncertainty aversion, we presented the payoff matrix experiment in table 5.4. The same payoff matrix is presented at first, without providing information regarding the distribution of probabilities of payoffs**.** An individual switches from a risky option to a riskless option in round *k* without knowing the probability of winning and losing lottery payoffs. It is assumed that individuals formulate subjective probability of winning and losing draw**.** Next, the same experiment was presented to the individual with known probabilities of winning and losing payoffs. In both experiments, it is assumed that individual utility is equivalent at the switching point. Suppose an individual prefers to switch from risky to riskless in both experiments. At this point, winning and losing payoffs from drawing the lotteries are $y_{1j,B,}$ and $y_{2j,B,}$ respectively, and the fixed payoff in the lottery is $x_{A,}$ and $U(x_A)$ is the utility derived from the certain payoff. Given these experiments where certain payoffs are equivalent in both experiments, uncertainty arises in the event due to unknown probability distribution, and the uncertainty aversion parameter is represented as δ. Now, it is important to know that the uncertainty response of an individual switching from lottery to a certain option in the experiment at point *j*, is captured by utility function:

$$U(x_A) = [\,U(y_{1j,B,}\, y_{2j,B;}\, p, q, \alpha,\ \gamma)]^{\delta} \qquad (5.6)$$

where, $y_{1j,B,}$ and $y_{2j,B}$ are winning and losing payoffs for the uncertain lotteries at round *k; p* and *q* are respective probabilities, and α, and γ are risk aversion and probability weighting parameters. Further, suppose uncertainty is absent, and an individual has all the information about the probability of payoffs. In that case, the individual prefers to switch certain risky payoffs of preferring lottery in round *k* in the experiment. Therefore, in a risky situation, the utility at point *k* is

$$U(x_A) = [\,U(y_{1k,B,}\, y_{2k,B;}\, p, q, \alpha,\ \gamma)] \qquad (5.7)$$

Now, given that the utility of the lottery for both experiments is equivalent to certainty $U(x_A)$. This can be written as,

$$U(x_A) = [\,U(y_{1j,B,}\, y_{2j,B;}\, p, q, \alpha,\ \gamma)]^{\delta} = [\,U(y_{1k,B,}\, y_{2k,B;}\, p, q, \alpha,\ \gamma)] \qquad (5.8)$$

With the given utility function taking logarithms on both sides, this can be written as

$$\delta \, log \, [\, U(y_{1j,B,} \, y_{2j,B;} p,q,\alpha, \gamma)] = log \, [\, U(y_{1k,B,} \, y_{2k,B;} p,q,\alpha, \gamma)] \tag{5.9}$$

$$\delta = \frac{log[U(y1j,B,y2j,B;p,q,\alpha,\gamma)]}{log[\, U(y1k,B,y2k,B;p,q,\alpha,\gamma)]} \tag{5.10}$$

where δ >1 in the case of uncertainty aversion. Here, it is important to note that other parameters α, and γ can be estimated from other experimental procedures, described in the next section.

5.3.4 Experimental Procedure of Uncertainty Measurement

The following experiment with payoff matrix in table 5.4 is inspired by Eckel & Grossman's (2003) and HL experimental procedures. This experimental instrument is designed to measure uncertainty aversion as depicted in 11 binary of fixed and uncertain options. The experiment on the left side presents the payoff of Rs. 200 with certainty. The right side of the experiment contains a lottery with an equal probability of winning Rs. 400 if the black ball is picked or Rs. 200 to Rs.10 if the red ball is picked. The respondents started to choose from row one with unknown probabilities (they must be unaware of the probabilities of the black and red balls in the first trial of the game). The game is designed in a cardinal order with a meaningful order of magnitude. A respondent once switches his preference, he has no incentive to switch it again. Thus, in experimental design, the game of the right-hand side is uncertain because subjects do not know the probability distribution over outcomes. In the next trial of the game, respondents were aware of the probability of payoffs. The information gap in the probability distribution leads respondents to take a lower risk than the risk aversion. It is called uncertainty aversion. There are also other methods available, and one of the popular ones is a BDM procedure in which subjects have to individually report to measure the valuation of a gamble (Becker, Degroot, & Marschak, 1964).

While introducing this lottery experiment, it is important to note that these two experiments were actually the first two experiments in all experiments conducted. It was to minimize the potential subjective expectation biases caused by experiences with earlier experiments.

Given such experiments conducted on rural farmers in India, it was important to ensure that farmers understood the rules before the final experiment started. Therefore, instructions were read aloud during the experimental sessions, and a written copy of instructions in their language was shared. We ensured that instructions were orally delivered to those participants who could not read and write. We also provided more elaboration if required and ensured that participants were the heads of the households making agricultural decisions.

Table: 5.4 *Payoff Matrix of Table Four*

	Fixed	**Unknown**	
		Black	**Red**
1.	200	400	200
2.	200	400	160
3.	200	400	130
4.	200	400	100
5.	200	400	80
6.	200	400	70
7.	200	400	60
8.	200	400	50
9.	200	400	40
10.	200	400	20
11.	200	400	10

#This table presented two times with known and unknown probabilities.

The experiment begins with a practice session, exclusive of the final game. The primary purpose of these preliminary sessions was to help participants understand the basics of the experiment. The experimental session was conducted with small groups of participants gathered at convenience at the village primary school with the help of local support. In this study, we consecutively conducted five experiments in the session, as explained above. The first was designed to measure uncertainty aversion behaviors, the second to measure risk aversion behaviors, and the third to measure loss-averse behavior. In an uncertainty experiment, the probabilities of respective payoffs were unknown, whereas, in a risky experiment, payoffs and probability were both known to the respondents. Further, loss aversion experimental measures were designed to include losses (negative payoffs) for decision-makers while making decisions. The decisions were taken under the condition of loss prospects. The survey was completed after the experiment, and payoffs were provided randomly selected rows for all the games.

5.4 Econometric Model

After accounting for each respondent's risk and uncertainty aversion value, we first observe the determinants of seed diversification in the current year. It is argued that farm and farmers' characteristics are important determinants of seed selection in the short run. This study includes simple OLS regression for all risk variables:

$$Yi = RA_i \, \varphi_{RA} + PW_i \, \varphi_{PW} + LA_i \, \varphi_{LA} + UA_i \, \varphi_{UA} + Z'_i \, \chi_i + \epsilon_i \tag{5.11}$$

In the equation, *Yi* denotes the number of seeds varieties of paddy a farmer adopts during the current season. Farmers generally adopt many varieties of seeds considering agroclimatic condition, profitability and risk factor. *Xi* is a vector containing prospect theory risk parameters, i.e., risk aversion (RA), probability weighting (PW), uncertainty aversion (UA), and loss aversion (LA), and φ_{RA}, φ_{PW}, φ_{LA}, and φ_{UA} denote coefficients for given risky variables. Risk aversion and loss aversion are divided into dummies into different categories: high-risk averse (less than 0.33), moderate risk-averse (0.67 to 0.34), less risk averse (0.99 to 0.66), and risk-neutral equal to 1. Similarly, loss aversion is divided into high loss averse (above 4), moderate loss averse (2.51 to 4), less loss averse (1.1 to 2.5), and loss neutral equal to 1. We found that most of the respondents were concentrated on moderate probability distortion (0.67 to 0.34) and less uncertainty aversion (see Figure 5.2); therefore, probability distortion and uncertainty aversion both are included as actual estimated parameters in the estimated. Further, Z_i is a vector of *i*th respondents' farm and farmers' characteristics, and χ_i denotes their coefficients, and ϵ_i denotes a stochastic disturbance term.

The main goal of this study is to understand how individual behavioral preferences influence the farmers' new seed adoption. This study does not focus on the demand for a particular paddy seed; instead, we analyze the farmers' adoption of new variety seed(s) for the current year and the adoption of new variety seed(s) continuously for the previous three years. Therefore, to analyze the effect of risk and uncertainty behavior in the decision of new seed adoption, we estimate the probit model,

$$P_i\,(p=1) \quad = \quad \frac{1}{Xi\beta 1 + Zi\beta 2 + \eta i} \tag{5.12}$$

Pi is the probability of adoption of new seed varieties in the current season of paddy production. Next, we also estimate the probability of new seed varieties of adoption for the last three years. This study also considers risk-seeking as irrational behavior; therefore, we have not included risk-seeking behavior in the model.

5.5 Results

5.5.1 Field Specification and Summary Statistics

This study was conducted in a specific region of the Indian state of Madhya Pradesh, the second-largest state in area situated in central India. This region boasts a rich and favorable agro-climatic environment and soil conditions supporting the cultivation of diverse crops and varied cropping patterns. It has emerged as one of the foremost agricultural states, registering the highest agricultural growth rate over the past decade. Paddy constitutes a significant component of the production during the monsoon season (Gulati et al., 2021). The Central and State governments have intervened through various policy initiatives to bolster the agricultural sector, redefining its food and farming strategies.

The primary aim of this study is to comprehend the demand for new seed varieties in paddy production, considering individual appetites for risk and uncertainty. Risk and uncertainty are inherent in agriculture and influence individual decision-making. Consequently, this study draws on two distinct data sources derived from a primary survey. Firstly, the survey encompasses descriptive statistics about farms and the characteristics of farmers. The second data source involves eliciting risk behavior through an experimental design to observe individual risk behavior. The comprehensive procedure of the experimental method is detailed in section 3, where it is meticulously expounded and carried out with local support. The experimental setup involved the household head responsible for all agricultural decisions, and relevant information regarding their background and agricultural activities was also collected. The study was conducted in the Rewa district, situated northeast of the state, with 147 farmers as respondents.

A pivotal aspect of the experimental data collection pertained to eliciting accurate preferences. Given our engagement with rural Indian farmers, it posed a challenge to capture their authentic preferences concerning risk and uncertainty behavior effectively. To overcome this, we opted for a pictorial method of communication, employing the local language. The live process of the entire experiment was presented, ensuring clarity and comprehensibility. Any queries or clarifications regarding the game procedures were addressed before the commencement of the final experiment. The study was initiated with a survey focused on individual and farm characteristics, which was followed by the execution of the experiment. The experiment was conducted during the paddy sowing season.

The experimental procedure adopted in this study follows the approach outlined by Ward & Singh (2015), which incorporates risk parameters encompassing a sequence of risk-free and risky choices with predetermined payoffs. This procedure is a revised version of the conventional TCN experimental method. The final game entailed choices involving risk in both options, with negative payoffs. Participants, in this case, the farmers, were informed that they would receive a specified percentage (10 percent) of the winning payoffs in each game. Importantly, this percentage was undisclosed to them during the game. They were instructed to select between option A and option B and were permitted to switch their choice only once within the series. Subsequently, their compensation was determined based on their choices.

A total of 150 samples were gathered to examine farmers and farm characteristics. Among these, only 147 samples were deemed suitable for inclusion in the study's analysis, as some respondents were excluded due to either invalid or insufficient information.

The descriptive statistics for farmer and farm characteristics data are presented in Table 5.5. The survey data collected for this study reveals that the average age of farmers responsible for agricultural decisions within the household is approximately 48.50 years. This group is predominantly male (94.56%), while female representation is nearly negligible. Consequently, the variable of gender has been excluded from the estimation. Regarding education, 30.61% of respondents indicated no formal education, 57.14% reported having received some schooling and the ability to read and write, and 10.88% mentioned having a college degree. The mean household size involved in agricultural activities was 3.48. Similarly, the approximate average annual income of the family was reported to be 3.91 lakhs, with around 23.64 respondents indicating engagement in farm activities, on average.

Table 5.5 *Summary Statistics of Farmers and Farm Characteristics*

Farmers Characteristics			**Mean/Percentage**	**Sd. Dev.**
1.	Age	(years)	48.50	9.93
2.	Gender	(Male=1; Female=0)	94.56% Male	
3.	Education	(%)		
A.	No Education		30.61%	
B.	School (up to 12th)		57.14%	
C.	College		10.88%	
5.	People involved in agriculture (nos.)		3.49	1.63
7.	Annual household income	(lakhs)	3.91	3.42
8.	No of years involved in agri activities (years)		23.64	9.71
Farm Characteristics				
9.	Farm Size (in acres)		3.34	2.64
10.	Total expected farm income	(lakhs)	2.51	2.75
11.	Livestock	(nos.)	3.07	2.27
12.	Formal debt	(%)	37.41%	
Seed adoption				
A1.	Number of average seed varieties adopted current year in the paddy production			2.367
A2.	Farmers adopted new seed varieties during the current year			48.30%
A3.	Farmers adopted new seed varieties continuously for the last three years			18.37%

Various other farm-related factors, such as farm size, are also crucial determinants influencing diversification and the adoption of new seed varieties. Indian farmers predominantly belong to the small and marginal category, practicing subsistence farming. The survey data disclosed that the average landholding per household was 3.34 acres, with a variance of 2.64. Additionally, the mean approximate value of farm income and livestock per household was 2.51 lakhs, with a variance of 2.75. Household debt was also investigated, considering its sources. It was found that 37.41% of respondents had borrowed debt from formal sources, indicating a positive shift towards formal borrowing channels instead of informal sources like local moneylenders. This inclination towards formal sources could potentially align with the government's efforts to expand short-term formal credit within the agricultural sector[30].

Regarding seed varieties for paddy production, which reflects the agricultural decision-making process, farmers reported a preference for using a minimum of two seed varieties (2.367) in the current season. Approximately 48.30% of farmers preferred incorporating new seed varieties in their seed selections for the current year. While only 18.37%, in comparison, new seed varieties have been continuously included over the past three years.

5.5.2 Parameters Estimation

The explanatory variables about farm and farmer characteristics, as outlined in Table 5.5, highlight that most farmers predominantly belong to the lower income bracket and possess micro and small landholdings. Consequently, these individuals are compelled to make decisions within an environment characterized by risk and uncertainty, with direct impact on their livelihoods. An assessment of farmers' risk behavior, utilizing the experimental method, was conducted, and the outcomes for all parameters are presented in Table 5.6. The mean estimation of the risk-aversion parameter is calculated at 0.66. This observation underscores a substantial level of concavity, as depicted in Figure 5.1a. Estimating the three critical parameters of the prospect theory utility function, namely risk aversion, probability weighting, and loss aversion, follows the methodology by Tanaka et al. (2010). The average risk aversion parameter closely aligns with estimates by Tanaka et al. (2010) and Nguyen and Leung (2010), implying that, on average, farmers in developing countries exhibit risk-averse tendencies. Corresponding research carried out in developed countries, such as the studies by Zhao & Yue (2020) involving American farmers and Bocqueho et al. (2014) focusing on French farmers, have shown significantly lower estimated risk aversion parameters. This suggests greater concavity for gains and convexity for losses within the utility function.

[30] Indian agricultural witnessed short-term credit covered 100 percent of the input cost in agriculture from institutional sources in 2012-13 according to National Account Statistics. It has also found that such credit has diverted towards non-agricultural activities.

Table: 5.6 *Mean and variance of parameter*

	Parameters	Mean value	Variance
1.	Risk aversion (α)	0.660	0.313
2.	Probability weighting (γ)	0.665	0.147
3.	Loss aversion (*λ)*	3.288	2.14
4.	Uncertainty aversion (*δ*)	0.989	0.05

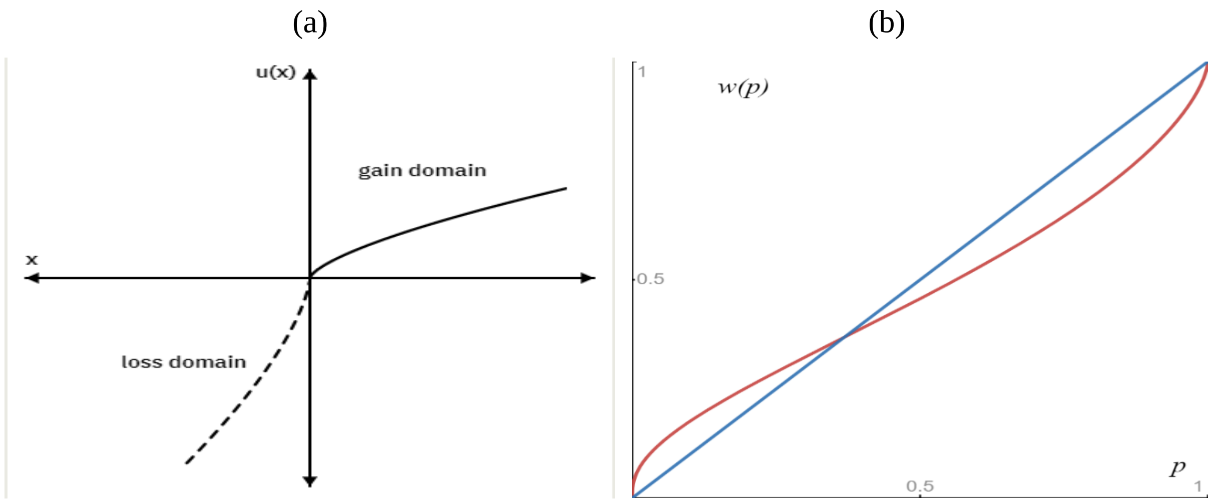


Figure 5:1 *PT value function (a) and PT weighting function (b)*

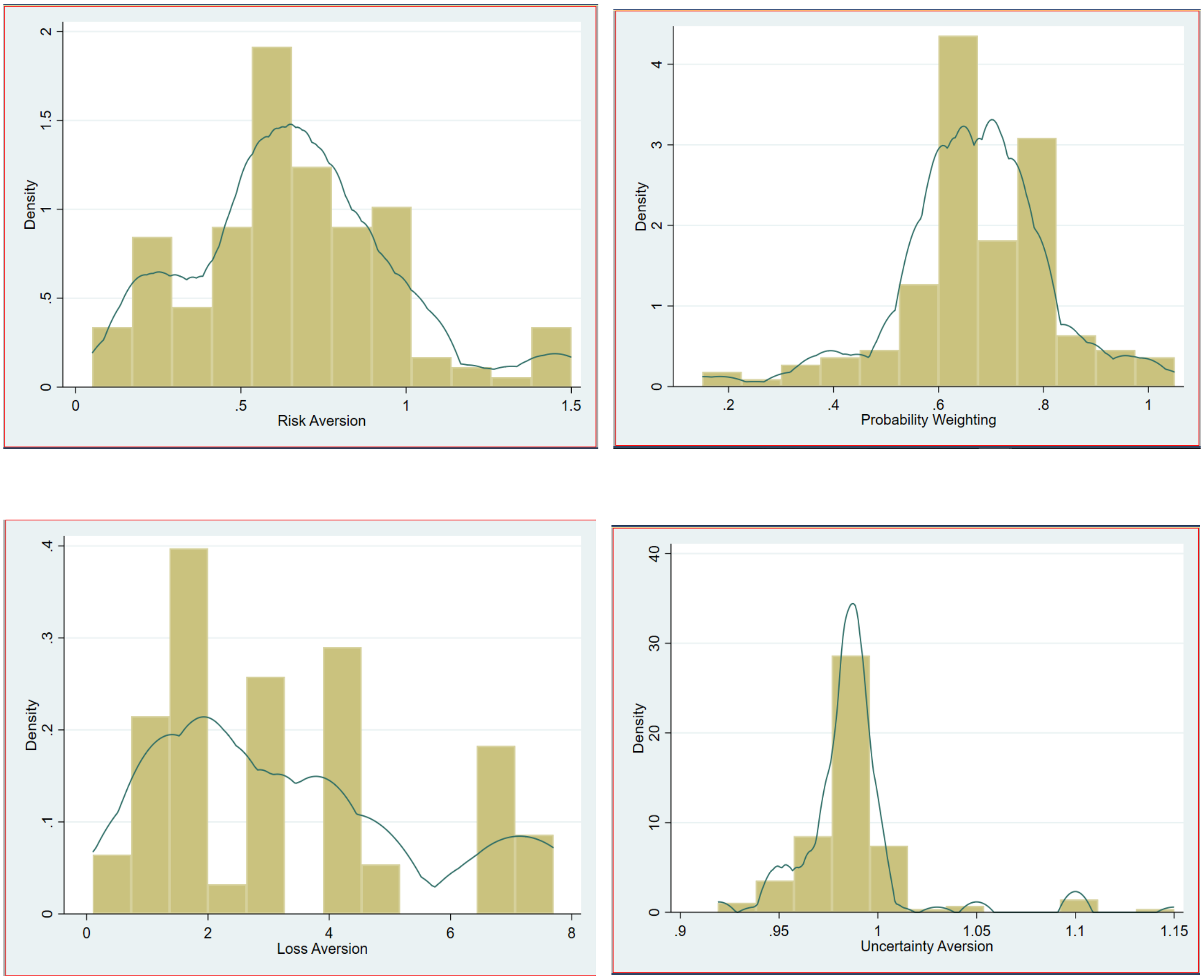


Figure 5:2 *Distribution of Parameters in Prospect Theory*

The estimated average probability weighting parameter (0.665) suggests that farmers tend to assign greater weight to small probabilities. This estimation of probability weighting closely resembles that found among Chinese farmers (Liu, 2013), French farmers (Bocqueho et al., 2014), and American farmers (Zhao & Yue, 2020). This pattern indicates that farmers consistently overestimate the significance of small probabilities across diverse contexts. The computed average value of the loss aversion parameter is 3.288, indicating a strong tendency among farmers to be loss-averse. This observation aligns with studies conducted among Vietnamese fish farmers (Nguyen & Leung, 2009) and Chinese cotton farmers (Liu, 2013).

Considering all the experimental procedures employed in this study, the CPT utility function proves flexible enough to capture preferences that comply with the expected utility. The premise of expected utility theory asserts that loss aversion and probability weighting equal 1. However, the estimated values for both these variables significantly diverge from 1, providing evidence to reject the linear probability weighting assumptions of expected utility theory in favor of the CPT model, characterized by the inverse-S shape probability weighting.

Two distinct experimental scenarios were conducted to compute the uncertainty aversion coefficient as defined in the earlier case. Respondents lacked awareness of the actual probabilities associated with respective payoffs. Instead, they provided estimations for the likelihood of winning a lottery despite an information gap. Most farmers exhibited uncertainty-averse behavior, although a few exhibited uncertainty-seeking tendencies, which were considered irrational and subsequently excluded from the estimation process of seed adoption. The resulting estimated uncertainty aversion coefficient equates to 0.989.

5.5.3 Diversification and Adoption of New Seed Varieties in Paddy Production

Table 5.7 presents results of the model of determinants of seed diversification, expressed in terms of the number of adopted seed varieties within the seed basket during the current paddy production season. Human actions and decisions constitute intricate processes, and the intricate interplay of institutions, technology, and local information shapes the determinants of diversification strategies. In the realm of farm decisions, farmers possess an intimate understanding of distinct local and traditional crop varieties. Often positioned at a vulnerable juncture, particularly in developing countries with subsistence economies, farmers are exposed to agro-climatic risks and constrained by limited resources. Given the multifaceted nature of local constraints, individuals are acutely attuned to selecting the optimal course of action, aligning their choices with their inherent risk attitude.

Through the results presented in the Table 5.8, an examination of the determinants of diversification is further facilitated. Notably, it is discerned that both high loss aversion and low loss aversion behaviors are statistically significant and positively associated with diversification. Conversely, low-risk aversion behavior is statistically significant and negatively related. This observation highlights that the inclination toward loss aversion holds more prominence than risk behavior. Consequently, farmers diversify their seed selections during paddy production to mitigate potential losses. The results also indicate

Table: 5.7 *Determinants of Seed Diversification in Paddy Production*

Variables	Diversification
High Risk Aversion	-0.152 (0.252)
Moderate Risk Aversion	-0.332 (0.224)
Low-Risk Aversion	-0.519** (0.243)
Prob. Distortion	0.051 (0.162)
Low Loss Aversion	0.672*** (0.206)
Moderate Loss Aversion	0.487 (0.314)
High Loss Aversion	0.353* (0.203)
Uncertainty Aversion	-0.167 (0.218)
Age	0.013 (0.011)
No Education	0.129 (0.250)
School Education (up to 12th class)	0.011 (0.233)
Number of People in agriculture	-0.007 (0.062)
HH Income	-0.007 (0.030)
No. of years involved in agri activities	-0.011 (0.011)
Agricultural Land (acres)	0.240*** (0.037)
Agri. Income	-0.049* (0.029)
Livestock	0.038 (0.034)
Formal Debt	-0.068 (0.166)
Constant	1.265** (0.572)
Observations	145
R-squared	0.391

Note: Robust standard errors in parentheses

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

a negative correlation with risk aversion behavior across the spectrum. This implies that greater risk aversion among farmers leads to decreased incentive for diversifying paddy seeds. It is conceivable that those farmers who exhibit low-risk aversion belong to higher income brackets and are more willing to overlook risks up to a certain threshold while demonstrating sensitivity to losses.

The magnitude of the farm size emerges as another important determinant, demonstrating statistical significance and a positive correlation. Farmers possessing larger land holdings are more

Table: 5.8 *Effect of Farm and Farmers' characteristic in the Adoption of New Seed Varieties in Paddy Production*

Variables	**Current Year**	**Last Three Years**
High Risk Aversion	0.641* (0.349)	2.316*** (0.541)
Moderate Risk Aversion	1.006*** (0.347)	0.995 (0.635)
Low-Risk Aversion	0.063 (0.365)	0.414 (0.607)
Prob. Distortion	0.052 (0.248)	0.001 (0.335)
Low Loss Aversion	-0.012 (0.347)	0.903 (0.657)
Moderate Loss Aversion	0.449 (0.432)	2.404*** (0.761)
High Loss Aversion	-0.223 (0.327)	2.103*** (0.621)
Uncertainty Aversion	-0.513 (0.347)	-0.283 (0.505)
Age	-0.006 (0.017)	0.033 (0.024)
No Education	0.861** (0.411)	15.571*** (4.528)
School Education	0.543 (0.373)	14.489*** (4.605)
Number of People in agriculture	0.127 (0.087)	0.101 (0.120)
HH Income	-0.058* (0.035)	-0.091 (0.062)
No. of years involved in agri activities	0.004 (0.016)	-0.076** (0.033)
Agricultural Land (acres)	0.144** (0.066)	-0.218* (0.122)
Agri. Income	-0.019 (0.047)	0.500*** (0.190)
Livestock	0.073 (0.055)	0.170** (0.067)
Formal Debt	-0.463* (0.256)	0.595 (0.393)
Constant	-1.114 (0.924)	-19.74*** (5.008)
R-squared	0.4869	0.5044
Observations	147	147

Note: Robust standard errors in parentheses

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

inclined to diversify their paddy crops with various seed varieties. The findings reveal a negative association between agricultural income and diversification. This suggests that farmers who favor single-crop varieties benefit more from specialization than diversification.

Table 5.8 provides results for the determinants influencing the incorporation of new seed varieties into the seed basket, both within the current year and continuously over the past three years. In the second column, the outcomes unveil the factors affecting the adoption of new seed varieties in the ongoing production year. This analysis highlights the significance of risk aversion behavior as a factor in new seed adoption. Notably, high and moderate risk-averse farmers exhibit statistically significant a positive coefficient. Contrasting this, over the long term, loss-aversion behavior assumes greater significance. The findings demonstrate that high-risk aversion behavior bears statistical significance and a positive association with the sustained adoption of new seeds in paddy production over larger time horizon as well. Both high and moderate loss-aversion behaviors reveal statistical significance and a positive link with incorporating new crop varieties. This observation suggests that, over time, farmers with heightened loss aversion exhibit greater sensitivity compared to risk-averse counterparts during the ongoing production years.

The results indicate that educated and non-educated farmers exhibit statistical significance and a positive correlation, albeit varying degrees. This outcome implies that education does not significantly impact the long-term adoption of new seed varieties.

The demand for agricultural inputs is also contingent on farmers' credit constraints. Farmers in developing countries perpetually encounter credit limitations while striving to fulfill their input requirements in agriculture (Narayanan, 2016). This study's findings reveal that household income shows statistical significance, showing a negative relationship with the demand for new seed varieties within the current year while bearing no influence over the long term. Agricultural income is a statistically significant factor with a positive relationship, as observed in the long term. This implies that farmers' adoption of new seed varieties is positively influenced by their farm income in the long run. Farm size is also a significant determinant of seed diversification. Farm size exhibits statistically significant and a positive relation in the short term while revealing a negative association in the long term. Agricultural income and livestock similarly emerge as statistically significant factors positively linked to adopting new seed varieties when assessed in the long term.

This highlights that farmers, driven by the benefits of adopting new seed varieties, are incentivized to continue such practices.

Lastly, coefficient for formal agricultural credit is statistically significant and demonstrates a negative relationship during the current production season while assuming statistical insignificance in the long run. A recent report on agricultural credit highlighted the alignment between short-term agricultural credit supply and demand, attributed to governmental incentives via schemes such as the Kisan Credit Card (KCC) (Hoda & Terway, 2015).

5.6 Discussion

The advent of the green revolution has spurred process growth across various regions. On one hand, the success of the green revolution highlights the need for direct strategies to enhance productivity. These strategies encompass research and development endeavors focused on high-yield variety (HYV) seeds, enhancements in crop protection mechanisms against floods, droughts, and pests, and the use of fertilizers and pesticides. On the other hand, a suite of policy interventions geared towards risk reduction enjoys governmental support. The efficacy of these measures is intricately tied to farmers' awareness of and accessibility to such policies. The present study delves into studying adoption of new seed varieties within a specific crop, specifically paddy, employing the CPT risk behavior model in farm decision-making.

Major crops, rice, and wheat, have substantially benefited from research and development (R&D) initiatives to enhance productivity and nutritional content. According to data from the National Rice Research Institute (NRRI) website, India boasts over 1200 varieties tailored to distinct agro-climatic conditions, a number that continues to grow. It is pertinent to clarify that this study does not focus on adopting specific varieties but on new seed varieties within paddy production. A persistent practice of utilizing the same crop as seeds for the subsequent season undermines crop productivity in case of HYV seeds. Constrained by credit limitations and exposed to risks, farmers often exhibit reluctance to incorporate new seed varieties into their production strategies. The findings of this study illuminate that merely 48.30 percent of farmers have embraced new seed varieties within the ongoing season, with a mere 18.37 percent adopting them consistently over the last three seasons.

This investigation establishes that farmers demonstrating relatively higher risk aversion are inclined to integrate new seeds into their current season's seed adoption. However, loss-aversion behavior emerges as a more influential factor when observing long-term behavior. This suggests that farmers gravitate towards adopting new seed varieties to mitigate potential losses over time. The "Seeds for Needs[31]" initiative undertook extensive research to probe how crop diversity could alleviate climate change-related risks in Bihar. The study underscored the significance of bridging information gaps and facilitating access to various seed varieties across crops. This approach empowers farmers to select crops and seed varieties best suited to their specific conditions, mitigating risks from unpredictable weather. While farmers diversified their seed crops, they concurrently expressed limited awareness regarding the myriad varieties available in the market.

Previous studies concerning the adoption of new seed varieties have predominantly focused on specific crops, such as Bt cotton (Liu, 2013), genetically modified corn, and soya (Barham et al., 2014). These investigations sought to ascertain the timeframe within which farmers embraced these novel varieties. To accomplish this, Weibull distribution[32] was employed, permitting the probability of adoption to fluctuate over time.

Interestingly, the findings of this study highlight that the probability distortion factor does not appear to exert a discernible influence on diversification or seed adoption. While farmers tended to overestimate small and relatively larger probabilities, this phenomenon did not substantially shape their diversification or adoption patterns. Another critical determinant of diversification is farm size. It is widely acknowledged that farmers with large land holdings can diversify and incorporate new seeds into their practices, thereby taking calculated risks into account.

The Indian agricultural landscape is marked by a majority of small-scale farmers who cultivate modest land areas for consumption. This contrasts with larger landholders who operate within industrialized production systems, focusing on meeting market demand. Small farmers frequently grapple with credit constraints and information gaps that hinder their diversification efforts. These

[31] This program is an initiative of Consultative group for International Agricultural Research (CGIAR) program on climate change, Agriculture and food security, funded by International Center for Tropical Agriculture (CIAT) see. https://www.bioversityinternational.org/news/detail/seeds-for-needs-india-a-pathway-to-diversification/

[32] Weibull distribution is defined as continuous probability distribution that captures the survivability of events over time (see Liu, 2013).

constraints also impact their ability to navigate climatic risks and bolster productivity. Interestingly, the study's outcomes also reveal a negative correlation between agricultural income and seed diversification within the current season. This potentially underpins the negative association observed between agricultural incomes and the adoption of new seed varieties during the ongoing season. This could arise from farmers' challenges in identifying the most appropriate crops for specific agro-climatic zones, leading to short-term losses. However, the results highlight farmers' positive long-term gains from adopting new seed varieties.

Furthermore, this study encompassed the aspect of uncertainty aversion behavior, a concept employed to differentiate it from risk. In the realm of agricultural decisions, uncertainty emerges as a pervasive phenomenon. Farmers grapple with incomplete knowledge concerning the probabilities linked to potential outcomes (Hardaker et al., 1997). This interpretation resonates with Knight's delineation of risk and uncertainty, accompanied by the subjective understanding of probability (LeRoy et al., 1987). As farmers engage in adoption decisions, they contend with an absence of perfect information about production distribution. Consequently, uncertainty emerges as a pivotal factor influencing the adoption of new seed varieties. Notably, this investigation establishes that uncertainty bears no statistical significance and exhibits a negative association. In contrast, Barham et al. (2014) identified consistent behavior with uncertainty playing a decisive role in adopting Bt. Cotton among US farmers. This divergence potentially stems from the heightened hesitancy to adopt new technologies within developing nations.

Examining new seed adoption within the current production season unveils a trend where embracing new seed varieties appears to constitute a strategy to mitigate risks. Farmers with relatively high risk aversion tend to opt for new seed varieties to mitigate the risk. The negative correlation with household income suggests that farmers might be disinclined to allocate resources to agricultural pursuits. This may be attributed to the presence of non-farm income sources. Research has highlighted that farmers are more prone to diversify their income streams through non-agricultural activities (Kapoor & Kapoor, 2022), a response prompted by the agricultural sector's persistent challenges. However, it is worth noting that farm income demonstrates a positive correlation with adopting new seed varieties.

Formal debt shows a negative association. A report scrutinizing formal debt in agricultural credit unveiled that government policies had effectively met the short-term agricultural credit demand (Hoda & Terway, 2015). Notably, this report also highlighted a notable credit shift towards non-agricultural activities.

Analyzing the consecutive three-year adoption of new seed varieties presents a nuanced perspective. It unveils substantial disparities in the prolonged adoption of new seed varieties. These findings indicate a divergence in the significance of explanatory variables between the current year's adoption and the long-term adoption trends. Interestingly, the data suggest that the adoption patterns of the current year may not necessarily hold the same significance over the long run.
Upon closer examination, it becomes apparent that farmers lacking formal education displayed a propensity to adopt new seed varieties in the current year. However, this inclination did not translate into the long run. In contrast, educated farmers were ready to embrace new seed varieties over the long term, displaying consistent responsiveness. Paradoxically, in the short run, educated farmers exhibited a certain degree of hesitancy in adopting new seed varieties.

These findings underscore the alignment between farmers' decisions to adopt new seed varieties and their risk attitude behavior, indicating that integrating new varieties is a valuable risk mitigation strategy.

Turning our attention to the determinants of farmers' risk attitudes using the prospect theory framework, the study reveals that probability weighting and uncertainty aversion do not yield statistically significant results. In the context of this investigation, these factors do not appear to be determinants of new seed variety adoption.

5.7 Conclusion

Plant scientists and policy-makers strive to bring about positive transformations in the well-being of impoverished farmers. Occasionally, their research endeavors yield groundbreaking advances, potentially enabling increased food production with reduced risk and lower costs. However, a hurdle may emerge from farmers' reluctance and weak response towards adopting innovations and technologies. This study underscores the importance of risk attitude and its profound influence on farmers' decision-making processes.

A continuous pressure to elevate production technology, shifts in governmental policies, the dynamic landscape of competition, and evolving markets have collectively led to greater complexities in agricultural decisions. These complexities are particularly pronounced for farmers in developing nations. Consequently, adopting new seed varieties emerges as a strategic response to curtail potential losses over the long term.

Chapter 6

Conclusion and Policy Implications

The main focus of this dissertation is understanding farmers' risk preferences and strategies by applying an alternative model to expected utility theory. This study used the prospect theory framework in the analysis of risk preferences. This study has an empirical and methodological focus. The dominant view on the methodological and empirical approach used for studying risk behavior among farmers does not adequately deal with the complexity of agricultural decisions. This study tries to understand the actual decisions under risk and uncertainty. Prospect theory and experimental methods provide an alternative approach to eliciting risk preferences. In this study of identifying risk behavior, we used the HL experimental procedure to capture risk preferences and observe its implication in farm decision-making.

A conceptual framework of risk behavior has been constructed, i.e., risk perception and attitude towards risk can be better understood through real-world decision experience. Behavioral and experimental methods have differentiated subjective risk. A study to compare risk attitude of farm owners with non-farm owners and the general population in the USA found significant heterogeneity (Roe, 2015). This might be caused by experiences and risk exposure to occupational differences.

Subjective risk comprises more than information transfer about risk factors. Hardaker and Lin (2010) highlighted the importance of subjective probability, a farmer's perceived likelihood of occurrence to risky phenomena in real-world agricultural decision-making scenarios. An assessment of subjective probability in the study of agricultural risk is potentially applied for which frequency data is unavailable. It includes the decision-maker's mental model - a framework for understanding real-world phenomena - assessing and filtering information influenced by past empirical incidents and contextual variables. Furthermore, the response of risk is not uniformly understood as the expected utility model presumes with too general a model. Prospect theory generalizes the expected utility model into risk and loss scenarios.

The first objective of this dissertation is to contribute to a better understanding of the theoretical model for study farmers' behavior. It is argued that the expected utility model and prospect theory are consistent in explaining the risk behavior in a simple experimental procedure. The prospect theory contributes to understanding the significant role of probability weighting in understanding risky behavior. It is an important behavioral characteristic that signifies the role of individuality in decision-making. This study found significant probability distortion behavior inconsistent with the inverse S-shape probability weighting function. We found that farmers were overemphasizing more on high probability rather than low probability as Tversky and Kahneman (1992) proposed. This study included decision-maker orientation of family cooperation to capture the collective decision–making. It is considered an indicator of human capital that might be helping improve the decision quality among farmers, which leads to improving their overall well-being. This study found farmers' and farm characteristics have no significant role in the determination of risk attitude in the PT model. Probably, it needs to be further examined how the potential risk management strategy is derived from the individual capacity, i.e., available resources, information, government policies, and regulations.

Another empirical contribution of this study is the analysis of the experimental methods. This study used the Tanaka Camerer and Nguyen (TCN) experimental method which is also derived from the original HL experimental procedure. Both these methods have been extensively used in the recent analysis of risk behavior in various contexts. We found, interestingly, a significant difference in the measurement of risk curvature parameters. Measurement of risk curvature through the HL experimental method reflects extreme risk aversion behavior (0.210), compared to the TCN procedure (0.61), although respondents belong to same socio-economic background in the same region.

This empirical study investigates the role of risk attitude in response to adopting MSP crops in the production decision. The implementation of MSP as an important policy measure to reduce price risk suggested that only 6 percent of farmers benefited by selling their crops directly to the government at all India levels (2012-13). The report also highlighted that only 16 percent farmers in Madhya Pradesh directly benefited by selling their crops to the government. The present study highlighted the significant role of MSP in farm decision-making. Perhaps MSP helps farmers get better prices by improving their bargaining power. The survey data reported that 20 percent of farmers were completely following the MSP in the production decisions, whereas 45.52 percent were considering a mix of MSP and non-MSP items in the production decision. This indicates that the MSP has a significant effect, more than the NSSO report reveals. This is consistent with the traditional economic theory that price information increases access to overall markets by lowering the search cost. As behavioral economics suggests, the possible welfare implication is through the psychological anchoring effect on the bargaining power matters.

Another significant finding of this study is that loss aversion is significant in explaining the adoption of MSP crop items in the production decision. A general argument is that farmers adopt MSP crop items to reduce price risk. However, this study enriches our understanding that both loss aversion and risk aversion behavior are statistically significant, and loss aversion is significantly more important in explaining the adoption of MSP crop items. The result is consistent with the argument that farmers adopt MSP crop items as an effective tool to reduce their losses due to price volatility.

The adoption of non-MSP items in the production decision is significant among Indian farmers. For example, Indian farmers have been witnessing a sudden fall in the price of onion and potato crops during the production season. These sudden falls in prices cost heavy losses, which must have an impact on farmers' production decision-making. When farmers try to sell their non-MSP products in the absence of MSP, they have no reference point and the power to bargain in the open market. More recently, in the study of farmers' risk behavior, farmers dared to take higher risks if they realized the prospect of new items (Maertens, Chari, and Just 2014). This is because some farmers manage to get a higher return if prices go up in a highly volatile market. Perhaps the adoption of highly risky crop items has been less explored in the context of Indian farmers. It might be the cause of farmers' loss aversion and willingness to take higher risks, or volatility might be an incentive to make an extraordinary profit. This needs to examine the farmers' risk behavior in the adoption of highly risky crops.

The theoretical advancement is to include human awareness of nature and society to enhance the ability to resist unintended events. An approach to reduce risk and uncertainty has been well developed due to the fast development of modern information sciences & technology. Perhaps PT model is better equipped to capture the scenarios of decision being taken in agriculture. In another study, we observed risk and uncertainty behavior among farmers to analyze its effect on seed adoption decisions in the same region. The study reveals significant uncertainty aversion behavior among farmers but does not find it to be significant in determining farmers' strategies to adopt new seed varieties in paddy production. We find that loss aversion behavior is significant in the adoption of new seed varieties in paddy production in the long run. This reflects that farmers use new seed varieties to minimize losses in the long run, but only a small proportion of farmers adopt this strategy. This might be due to an information gap about seed varieties and the benefits of adopting new seed varieties. Probably a small effort to make awareness of the advantage may have significant effect in the agricultural productivity as well as growth.

This study reveals the significance of risk and uncertainty in decision-making in the context of agricultural decisions. It highlights the importance of alternative methods in the literature for analyzing risky behavior in agricultural decision-making.

It is also important to note that this study covers specific scenarios within the state of Madhya Pradesh, and its findings may or may generalized across all of India. However, there is scope to analyze risk behavior across India, examining how farmers generally respond to various policy initiatives aimed at mitigating risk and uncertainty. Farmers across different states face varied socio-economic and agro-climatic challenges. Therefore, studying a broader perspective on risk behavior among farmers would be of interest to policymakers and academics alike.

Agriculture holds new challenges and opportunities. It is needed to conduct research on risk and uncertainty dealing with persons’ different manners of dealing with risk and uncertainty. It may provide more accurate prediction of individual choices. The fact that, a society is more heterogeneous in real life, and some people have less liabilities of social forces than others. Therefore, farmers’ dealing with a risk and loss situations vary. Probably, minimizing in the loss scenario may entail significant changes in the decision-making.

Appendix 1A

Risk Behavior among Farmers: Expected Utility and Prospect Theory Approach

Detail Procedure of the Survey and Experiments

Thank you all for participating in this survey and experiment. This is a study about farmers' cognitive ability and its role in risk behavior and repercussions of farmers' well-being due to their decision-making. We are here to collect information about risk attitudes and some personal and farm-related information. Therefore, this process consists of two parts; you will be asked about personal information and farm-related activities in the first part. In the second part, you will join the experiments of two known probability situations. Experimental procedures are given below, and you have a chance to win the prize in the game based on your choice and your luck. The amount will be paid after the completion of the experiment. The payment will be a fraction of the total winning amount of the experiment. The fraction is already decided and written separately in the envelope. It will be disclosed after the end of the experiment. You can leave the experiment at any point if you want to leave it. The experimental method will be explained below, with a live example, so it is important that you listen carefully as possible. You will be asked to come to another room individually for the final experiment. The information you will share with us will be confidential and will not be shared with anyone. This information will be used only for academic purposes.

If you have any queries or cannot understand the process, please feel free to ask at any time. The questionnaire, as well as the experimental choice options, will be given to the respondents. To complete the questionnaire, the experiment will take around 30 minutes.

Part 1

(**Questionnaire for Socioeconomic Characteristics)**

Farmers' Characteristics

1. Name ____ 2. Age______________________

3. Gender _____________________, 4. Household Size_____________________________

5. Education Level No______, 1 to 12th _________, Graduation _____________________

6. Number of people directly involved in Agriculture _______________________________

7. Number of school/college-going children in household __________________________

8. Annual expenditure on education ____

9. Total expected family income ____

10. No. of years involved in farm activities____

11. Do you include family members in the process of agricultural decision, if yes, 1/________

12. Number of rooms in the house ____

Farm Characteristics

13. Farm size ____

14. Land ledge from other ____

15. Land ledge to other ____

16. Total expected farm income ____

17. Number of livestock ____

18. Do you have debt from informal sources? if Yes, 1 _________________________________

19. Do you have debt for formal sources? if Yes, 1 ___________________________________

Process of experiment

Your objective in these activities is to win a money prize. To win the prize, you have to make a choice between two options, high-risk and low-risk prospects, and the winning and losing amount is determined by a random draw. Given the choice experiment in row (Table1), option plan A consists of the amounts with known probabilities, i.e., only 10 percent chance of getting payoff rupees 250, and 90 percent chance of getting payoff rupees 100. Similarly, to counter against option A, plan B consists of a 10 percent chance of getting payoff rupees 400 and 90 percent chance of getting 10. The respective probabilities are mentioned in the form of black and red balls. Your goal is to make a choice in each row between Plan A and Plan B in the experiment. You can switch plans between A and B only once.

Table 1

	Plan A		**Plan B**	
1.	**250 if** **100 if**		**400 if** **10 if**	

For example, given in table 2 a series of 10 rows, you have to choose plan A or plan B in all ten rows. Once you choose your plans, the prize you will receive in each row will depend on the number that you draw from ten cards; as I am showing each card has its own number from 1 to 10.

Now you can see an example, how a lottery prize can be earned. For example, suppose you have chosen plan A in row 2. Then you draw a single card among 10 cards which consist of 2 black and 8 red. If the card is black, you will earn 180, and if it is red, you will earn 140.

Similarly, if you choose plan A in row 4, and single draw among the 10 cards will be conducted. But, the number of black cards in all ten cards will be 4. It means that the chances of getting the black card is higher than row 2. Similarly, if you choose plan B, similarly, if you look at row 5, all black and white cards are equal. It means that chances of getting black and white cards are equal.

Similarly, in row seven, the chances of getting the maximum amount are higher because the number of black balls is 7 out of the ten balls.

Finally, in the last row, row 10, all balls are black regardless of the payoffs associated with each plan, either plan A or plan B.

Remember, the payment will be made only once, which will be randomly drawn from the available rows through cards 1 to 10 as presented above. Therefore, once you have made all the choices, you will choose a particular row for payment, and the game will be played according to a particular row available black and white balls.

Table 2

	Plan A			**Plan B**		
1.	**180 if** **140 if**	● 🔴 🔴 🔴 🔴 🔴 🔴 🔴 🔴 🔴		**350 if** **10 if**	● 🔴 🔴 🔴 🔴 🔴 🔴 🔴 🔴 🔴	
2.	**180 if** **140 if**	● ● 🔴 🔴 🔴 🔴 🔴 🔴 🔴 🔴		**350 if** **10 if**	● ● 🔴 🔴 🔴 🔴 🔴 🔴 🔴 🔴	
3.	**180 if** **140 if**	● ● ● 🔴 🔴 🔴 🔴 🔴 🔴 🔴		**350 if** **10 if**	● ● ● 🔴 🔴 🔴 🔴 🔴 🔴 🔴	
4.	**180 if** **140 if**	● ● ● ● 🔴 🔴 🔴 🔴 🔴 🔴		**350 if** **10 if**	● ● ● ● 🔴 🔴 🔴 🔴 🔴 🔴	
5.	**180 if** **140 if**	● ● ● ● ● 🔴 🔴 🔴 🔴 🔴		**350 if** **10 if**	● ● ● ● ● 🔴 🔴 🔴 🔴 🔴	
6.	**180 if** **140 if**	● ● ● ● ● ● 🔴 🔴 🔴 🔴		**350 if** **10 if**	● ● ● ● ● ● 🔴 🔴 🔴 🔴	
7.	**180 if** **140 if**	● ● ● ● ● ● ● 🔴 🔴 🔴		**350 if** **10 if**	● ● ● ● ● ● ● 🔴 🔴 🔴	
8.	**180 if** **140 if**	● ● ● ● ● ● ● ● 🔴 🔴		**350 if** **10 if**	● ● ● ● ● ● ● ● 🔴 🔴	
9.	**180 if** **140 if**	● ● ● ● ● ● ● ● ● 🔴		**350 if** **10 if**	● ● ● ● ● ● ● ● ● 🔴	
10.	**180 if** **140 if**	● ● ● ● ● ● ● ● ● ●		**350 if** **10 if**	● ● ● ● ● ● ● ● ● ●	

Appendix 1B

Codes for the Estimation

Model 1

```
*define expected utility model on Holt Laury method
*define program name
program define HL_eu
*specify the argument of the program
args lnf r mu
*declare the temporary variables to be use in the model
tempvar theta lnfj prob1l prob2l prob1r prob2r euL euR y1 y2 y3 y4 euDiff

quietly{
*initializing the ML data*/
generate double `prob1l' = $ML_y2
generate double `prob2l' = $ML_y3
generate double `prob1r' = $ML_y4
generate double `prob2r' = $ML_y5

*define utility function*/
gen double `y1' = ($ML_y6)^(`r') if $ML_y6>=0
gen double `y2' = ($ML_y7)^(`r') if $ML_y7>=0
gen double `y3' = ($ML_y8)^(`r') if $ML_y8>=0
gen double `y4' = ($ML_y9)^(`r') if $ML_y9>=0

* calculate EU of each lottery*/
gen double `euL' = (`prob1l'*`y1')+(`prob2l'*`y2')
gen double `euR' = (`prob1r'*`y3')+(`prob2r'*`y4')

*get the Fechner index*/
generate double `euDiff' = `euR' - `euL'

*likelihood function*/
replace `lnf' = ln(normal( `euDiff')) if $ML_y1==1
replace `lnf' = ln(normal(-`euDiff')) if $ML_y1==0
}
end

ml model lf HL_eu (r:Choice P1L P2L  P1R P2R Prize1 Prize2 Prize3 Prize4= ageI D1 D2 nof foA chld  YoAI FincmI
AincmI eduexpI Fdebt Ifdebt  part), cluster(ID) maximize difficult
ml display
```

Model 2

```
* define Prospect Theory model following Harrison and Rutstrom (2008)
program define ML_cpt
*specify the argument of the program
args lnf alpha gamma
*declare the temporary variables to be use in the model
tempvar prob0l prob1l prob0r prob1r y0 y1 y2 y3
tempvar euL euR euDiff euRatio tmp

quietly {
*define probability weighting
generate double `prob0l' = exp (-(ln($ML_y2)^`gamma')
generate double `prob1l' = exp (-(ln($ML_y3)^`gamma')


*define utility function
generate double `y0' =  ( $ML_y4)^(`alpha') if $ML_y4>=0
generate double `y1' =  ( $ML_y5)^(`alpha') if $ML_y5>=0
generate double `y2' =  ( $ML_y6)^(`alpha') if $ML_y6>=0
generate double `y3' =  ( $ML_y7)^(`alpha') if $ML_y7>=0

*generate Expected Utility
gen double `euL'= .
replace `euL'= (`prob0l'*`y0')+((1-`prob1l')*`y1') if $ML_y4>=0
replace `euL' =(`prob0l'*`y0')+(`prob1l'*`y1') if $ML_y4<0
gen double `euR'= .
replace `euR' =(`prob0r'*`y2')+((1-`prob1r')*`y3') if $ML_y6>=0
replace `euR' =(`prob0r'*`y2')+(`prob1r'*`y3') if $ML_y6<0

*get the Fechner index
generate double `euDiff' = `euR' - `euL'
*likelihood function
replace `lnf' = ln(normal( `euDiff')) if $ML_y1==1
replace `lnf' = ln(normal(-`euDiff')) if $ML_y1==0
}
end
ml model lf ML_cpt (alpha:  Choice  P1L P2L P1R P2R  Prize1 Prize2 Prize3 Prize4=  ageI D1 D2 nof foA chld YoAI
FincmI AincmI eduexpI  Fdebt Ifdebt part ) (gamma: ageI D1 D2 nof foA chld  YoAI FincmI AincmI eduexpI
Fdebt Ifdebt  part), cluster (ID) technique(nr)  maximize difficult
ml display
```

Appendix *2*

Risk attitude and response of MSPs in Production Decisions among Farmers: A Cumulative Prospect Theory Approach

Detail Procedure of the Survey and Experiments

Thank you all for participating in this survey and experiment. This is a study about farmers' risk behavior and its role in adopting a strategic decision in response to the Minimum Support Prices (MSPs). We are here to collect information about risk attitudes and some personal and farm-related information. Therefore, this process consists of two parts; you will be asked about personal information and farm-related activities in the first part. In the second part, you will join the experiments of two known probability situations. Experimental procedures are given below, and you have a chance to win the prize in the game based on your choice and partly luck. The amount will be paid after the completion of the experiment. The payment will be an average of the fraction of the total winning amount of all experiments. The fraction is already decided and written separately in the envelope. It will be disclosed after the end of the experiment. If you want to leave the experiment at any point, you can leave it. The experimental method will be explained below, with a live example, so it is important that you listen carefully as possible. You will be asked to come to another room individually for the final experiment. The information you will share with us will be confidential and will not be shared with anyone. This information will be used only for academic purposes.

If you have any queries or cannot understand the process, please feel free to ask at any time. The questionnaire, as well as the experimental choice options, will be given to the respondents. To complete the questionnaire, the experiment will take around 30 minutes.

Part 1

(**Questionnaire for Socioeconomic Characteristics)**

Farmers' Characteristics

1. Name ________________________________
2. Age__________________________________
3. Gender ______________________________
4. Household Size_________________________
5. Education Level No______, 1 to 12th ________, Graduation _____________

6. Total expected family income ______________________________

7. No. of years involved in farm activities______________________________

Farm Characteristics

8. Farm size ______________________ __________________________

9. Number of livestock ______________________________

10. I consider during the crop selection only the non-MSP-backed items; if yes, 1 ________

11. I consider during the crop selection both MSP and non-MSP backed items; if yes, 1 ________

12. I consider during the crop selection only MSP-backed items; if yes,1 ________________

Process of experiment

Your objective of these activities is to win a money prize. To win the prize, you have to make a choice between two options, high-risk and low-risk prospects, and the winning and losing amount is determined by a random draw. Given the choice experiment in row one (Table1), option plan A consists of the amounts with known probabilities, i.e., only 10 percent chance of getting payoff rupees 400, and 90 percent chance of getting payoff rupees 100 . Similarly, to counter against option A, plan B consists of a 30 percent chance of getting payoff rupees 260 and 70 percent chance of getting 50. The respective probabilities are mentioned in the form of black and red balls. Your goal is to make a choice in each row between Plan A and Plan B in all three series. You can switch plan between A and B only once in each series (Table 2). Once you make the choices in all three series, in all 33 rows. Then, you have to draw a single row option for payment randomly, and that particular row will be played for the final payment.

Tabel 1

	Plan A		Plan B	
1.	**400 if** **100 if**		**260 if** **50 if**	

Once you complete your record sheet of all three series experiments, the game will start. First, you have to draw a ball from Box 1, which consists of options with different numbers according to the numberof rows, and each card is marked with particular number. As, in game 1 these cards are marked from 1 to 12. This draw will partially determine your real money. Suppose you randomly draw the 4th ball in the Box. Then we will play question 4th for real money with the help of Box 2 consists of black and red cards. The number of black and red cards will vary according to the probability in Box 2.

Table 2

	Plan A			**Plan B**		
1.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**260 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
2.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**280 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
3.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**320 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
4.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**360 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
5.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**400 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
6.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴		**450 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	✓
7.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴		**560 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	✓
8.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴		**660 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	✓
9.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴		**720 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	✓
10.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴		**860 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	✓
11.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴		**1060 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	✓
12.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴		**1260 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	✓

To practice the game,

For example, to complete the record sheet, as presented below in Table 2. You have to choose between plan A or Plan B vonsidering the given payoffs and number of black and red balls in terms of respective probabilities. You have to choose in all rows of all three games, 1, 2, and 3, between Plan A and Plan B. For example, if you choose the first five rows of option Plan A, and the remaining seven rows of options Plan B, as presented in table 2. Further, if your randomly draw comes 4th row for actual payment from Box 1.

Table 3

	Plan A			Plan B		
1.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**260 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
2.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**280 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
3.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**320 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
4.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**360 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
5.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**400 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
6.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**450 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
7.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**560 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
8.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**660 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
9.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**720 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
10.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**860 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
11.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**1060 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	
12.	**400 if** **100 if**	⚫🔴🔴🔴🔴 🔴🔴🔴🔴🔴	✓	**1260 if** **50 if**	⚫⚫⚫🔴🔴 🔴🔴🔴🔴🔴	

Then, we draw the ball from another Box, which consists of one black ball and nine red balls. Suppose it draws a black ball from Box B, and as you have chosen Plan A in the series, then your prize will be 400. If it draws the red ball, your prize will be 100.

Further, if the 11^{th} row is drawn for actual payment, and you have chosen Plan B in the series consisting of three black and seven red balls. Then the game will be played, a ball will be drawn from the Box, in which you have a chance to get 1060 if it is drawn the black ball, and you will get 50 if you draw the red ball.

Similarly, if the 12^{th} row is drawn for actual payment, and you have chosen Plan B in the series consisting of three black and seven red balls. Then the game will be played; a ball will be drawn from the Box, in which you have a chance to get 1260 if it is drawn the black ball, and you will get 50 if you draw the red ball.

Next, there are negative payoffs in each plan in the last seven rows. You have to follow the similar procedure, you have to choose between plan A and plan B. Please look at it carefully.

Table 4

	Plan A		Plan B	
1.	**400 if** **100 if**		**280 if** **50 if**	✓
2.	**400 if** **100 if**		**280 if** **50 if**	✓
3.	**400 if** **100 if**		**320 if** **50 if**	✓
4.	**400 if** **100 if**		**360 if** **50 if**	✓
5.	**400 if** **100 if**		**400 if** **50 if**	✓
6.	**400 if** **100 if**		**450 if** **50 if**	✓
7.	**400 if** **100 if**		**560 if** **50 if**	✓
8.	**400 if** **100 if**		**660 if** **50 if**	✓
9.	**400 if** **100 if**		**720 if** **50 if**	✓
10.	**400 if** **100 if**		**860 if** **50 if**	✓
11.	**400 if** **100 if**		**1060 if** **50 if**	✓
12.	**400 if** **100 if**		**1260 if** **50 if**	✓

Your actual experiment starts from now; please choose the option Plan A or Plan B according to the instruction given above.

Game 1

	Plan A		Plan B	
1.	**400 if** **100 if**		**680 if** **50 if**	
2.	**400 if** **100 if**		**750 if** **50 if**	
3.	**400 if** **100 if**		**830 if** **50 if**	
4.	**400 if** **100 if**		**930 if** **50 if**	
5.	**400 if** **100 if**		**1060 if** **50 if**	
6.	**400 if** **100 if**		**1250 if** **50 if**	
7.	**400 if** **100 if**		**1500 if** **50 if**	
8.	**400 if** **100 if**		**1850 if** **50 if**	
9.	**400 if** **100 if**		**2200 if** **50 if**	
10.	**400 if** **100 if**		**3000 if** **50 if**	
11.	**400 if** **100 if**		**4000 if** **50 if**	
12.	**400 if** **100 if**		**6000 if** **50 if**	

In this experiment, please choose the option Plan A or Plan B according to the instruction given above.

Game 2

	Plan A		**Plan B**	
13.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**540 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
14.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**560 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
15.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**580 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
16.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**600 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
17.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**620 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
18.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**650 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
19.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**680 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
20.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**720 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
21.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**770 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
22.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**830 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
23.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**900 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
24.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**1000 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
25.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**1100 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	
26.	**400 if** ● ● ● ● ● **300 if** 🔴 ● ● ● ●		**1300 if** ● ● ● ● ● **50 if** 🔴 🔴 🔴 ● ●	

In this experiment, please choose the option Plan A or Plan B according to the instruction given above.

Game 3

	Plan A		Plan B	
27.	**250 if** **-40 if**		**300 if** **-210 if**	
28.	**40 if** **-40 if**		**300 if** **-210 if**	
29.	**10 if** **-40 if**		**300 if** **-210 if**	
30.	**10 if** **-40 if**		**300 if** **-160 if**	
31.	**10 if** **-80 if**		**300 if** **-160 if**	
32.	**10 if** **-80 if**		**300 if** **-140 if**	
33.	**10 if** **-80 if**		**300 if** **-110 if**	

Appendix: 3

Role of Risk and Uncertainty in Seed Adoption: A Cumulative Prospect Theory Approach

Detail Procedure of the Survey and Experiments

Thank you all for participating in this survey and experiment. This is a study about farmers' risk and uncertainty behavior and its role in adopting new variety seeds in paddy production. We are here to collect information about risk and uncertainty attitude and some personal and farm-related information. Therefore, this process consists of two-part; you will be asked about personal information and farm-related activities in the first part. In the second part, you will join the experiments of two different known and unknown probability situations. Experimental procedures are given below, and you have a chance to win the prize in each game separately based on partly your choice and partly your luck. The amount will be paid after the completion of all experiments. The payment will be an average of the fraction of the total winning amount of all experiments. The fraction is already decided and written separately in the envelope. It will disclose after end of experiment. If you want to leave the experiment at any point in time, you can leave it. The experimental method will be explained below, with a live example, so it is important that you listen carefully as possible. For the final experiment, you will be asked to come to another room individually. The information you will share with us will be confidential and will not be shared with anyone. This information will be used only for academic purposes.

If you have any query or cannot understand the process, please feel free to ask at any time. The questionnaire, as well as the experimental choice options, will be given to the respondents. To complete the questionnaire and experiment will take around 30 minutes.

Part 1

(Questionnaire for Socioeconomic Characteristics)

Farmers' Characteristics

1. Name ____
2. Age __________________
3. Gender_____________________,
4. Education Level No______, 1 to 12th _________, Graduation________________

5. Number of people directly involved in Agriculture ______________________________

6. Total expected family income ____

7. No. of years involved in farm activities____

Farm Characteristics

8. Farm size ____

9. Total expected farm income ____

10. No. of Livestock ____

11. Do you have debt for formal sources? if Yes, 1 or 0 ______________________________

12. Numbers of seed varieties used in the Paddy crop production in the current season_____

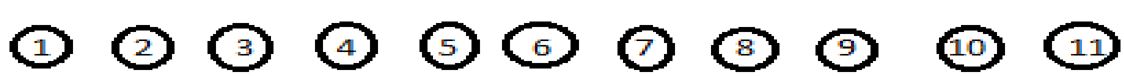
13. New seed varieties have been used this year in paddy production. Yes 1 otherwise 0______

14. New seed varieties you have used continuously since the last 3 years in the paddy production Yes 1 otherwise 0______

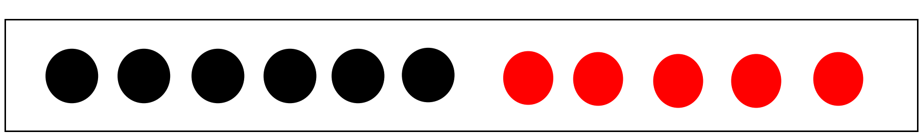
Process of Experiment 1

Your objective in these activities is to win the money prize. To win the prize, you have to make a choice between two options, a sure and two prospects with associated risk or uncertainty, and the winning and losing amount is determined by a random draw. Given the choice experiment, a risky option consists of known amounts with a known probability (Table 1), whereas uncertain prospects consist of the known prize and with unknown probabilities in terms of the number of the black and red balls. Your goal is to make a choice in each row between Plan A and Plan B. You can switch the plan between A and B only once in the series of all eleven questions (Table 2). You will be paid separately for each game at the end of the game.

Card 1 to 10



Box 2



Once you complete your record sheet of all five series experiments, the game will start. First, you have to draw a ball from Box 1, which consists of eleven balls, and each ball (option) has a different number. This draw will partially determine your real money. Suppose you randomly draw the 4th ball in the Box. Then we will play question 4th for real money with the help of Box 2 consists of black and red balls. The number of balls will vary according to the probability in Box 2. The number of black and red balls is unknown if there is an uncertain situation.

Table 1

	Plan A		Plan B	
1.	100		400 if ; 200 if	

Table 2

	Plan A		Plan B	
1.	100		400 if 200 if	✓
2.	100		400 if 160 if	✓
3.	100		400 if 130 if	✓
4.	100		400 if 100 if	✓
5.	100	✓	400 if 80 if	
6.	100	✓	400 if 70 if	
7.	100	✓	400 if 60 if	
8.	100	✓	400 if 50 if	
9.	100	✓	400 if 40 if	
10.	100	✓	400 if 20 if	
11.	100	✓	400 if 0 if	

To practice the game,

For example, to complete the record sheet, as presented in Table 2. In uncertain situations, you have to choose between plan A or Plan B with an unknown number of black and red balls. You have to choose all eleven questions in the table between Plan A and Plan B. Further, if you choose the first four questions of uncertainty (Plan B), and the remaining seven questions of fixed options (Plan A). If your randomly drawn item from Box 1 is 4th.

Then, we draw the ball from Box 2, which consists of 10 balls with two different colors (Black and White). Suppose it draws a black ball from Box B, and as you have chosen Plan A (uncertain option) in the series, then your prize will be 400. If it draws the red ball, your prize will be 100. Further, if the 2nd ball is drawn from Box 1 and you have chosen Plan B (uncertain option) in the series. The ball will be drawn from Box 2, and then you have a chance to get 400 if it is drawn the black ball, and you will get 160 if you draw a red ball.

Table 3

	Plan A		**Plan B**		
1.	100		400 if	200 if	✓
2.	100		400 if	160 if	✓
3.	100		400 if	130 if	✓
4.	100		400 if	100 if	✓
5.	100		400 if	80 if	✓
6.	100		400 if	70 if	✓
7.	100		400 if	60 if	✓
8.	100		400 if	50 if	✓
9.	100		400 if	40 if	✓
10.	100		400 if	20 if	✓
11.	100		400 if	0 if	✓

Similarly, if the 11th ball is drawn from Box 1 and you have chosen Plan A (riskless option) in the series, you will get 100 rupees for sure.

Next, suppose you choose Plan B (uncertain options) for all eleven questions in the table as presented in table 3. Further, in case if you draw the 1st ball from Box 1, the particular row will decide the prospects of prize payment. You have a chance of winning the prizes, either 400 or 200, according to the ball drawn from Box 2. If the ball is black, you will get 400, and if the ball is red, you will get 200.

Similarly, suppose you choose Plan A (riskless options) for all eleven questions, as presented in Table 4. In that case, you will receive 100 rupees for sure, and no game will be played.

Further, you have to follow a similar process to choose between Plan A and Plan B in Game 2, Game 3, and Game 4 with different but known probabilities. All, you will be known the number of black and red balls available in Box 2 (the number of black and red balls will vary).

In Game 5, only seven questions are available; therefore, in this case, Box 1 would contains only seven balls, you will draw the ball out of seven balls for this particular game. In this game, both Plan A and Plan B are risky; among them, there is a possibility of a negative prize where you can lose the amount. (Please look at game 5).

Table 4

	Plan A		Plan B		
1.	100	✓	400 if	200 if	
2.	100	✓	400 if	160 if	
3.	100	✓	400 if	130 if	
4.	100	✓	400 if	100 if	
5.	100	✓	400 if	80 if	
6.	100	✓	400 if	70 if	
7.	100	✓	400 if	60 if	
8.	100	✓	400 if	50 if	
9.	100	✓	400 if	40 if	
10.	100	✓	400 if	20 if	
11.	100	✓	400 if	0 if	

Your actual experiment starts from now; please choose the option Plan A or Plan B according to the instruction given above.

Game 1

	Plan A		Plan B	
1.	200		400 if 200 if	
2.	200		400 if 160 if	
3.	200		400 if 130 if	
4.	200		400 if 100 if	
5.	200		400 if 80 if	
6.	200		400 if 70 if	
7.	200		400 if 60 if	
8.	200		400 if 50 if	
9.	200		400 if 40 if	
10.	200		400 if 20 if	
11.	200		400 if 10 if	

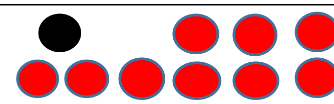
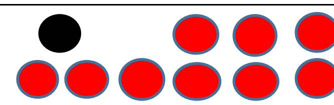
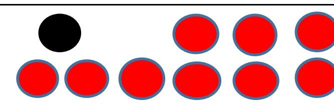
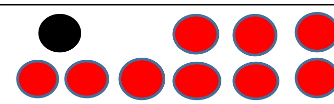
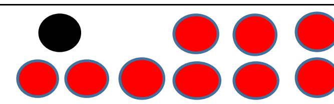
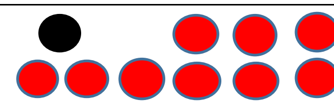
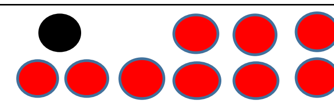
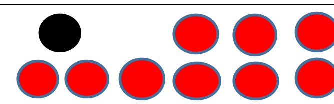
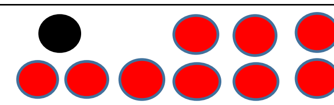
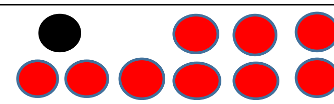
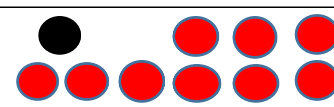
Please choose the option Plan A or Plan B according to the instructions given above.

Game: 2

	Plan A		Plan B	
1.	200		400 if 200 if	
2.	200		400 if 160 if	
3.	200		400 if 130 if	
4.	200		400 if 100 if	
5.	200		400 if 80 if	
6.	200		400 if 70 if	
7.	200		400 if 60 if	
8.	200		400 if 50 if	
9.	200		400 if 40 if	
10.	200		400 if 20 if	
11.	200		400 if 10 if	

Please choose the option Plan A or Plan B according to the instruction given above.

Game: 3

	Plan A		Plan B		
1.	100		260 if 50 if		
2.	100		280 if 50 if		
3.	100		320 if 50 if		
4.	100		360 if 50 if		
5.	100		410 if 50 if		
6.	100		470 if 50 if		
7.	100		560 if 50 if		
8.	100		630 if 50 if		
9.	100		720 if 50 if		
10.	100		850 if 50 if		
11.	100		1330 if 50 if		

Please choose the option Plan A or Plan B according to the instruction given above.

Game: 4

	Plan A		**Plan B**	
1.	400		560 if 50 if	
2.	400		570 if 50 if	
3.	400		600 if 50 if	
4.	400		620 if 50 if	
5.	400		650 if 50 if	
6.	400		690 if 50 if	
7.	400		730 if 50 if	
8.	400		770 if 50 if	
9.	400		820 if 50 if	
10.	400		870 if 50 if	
11.	400		950 if 50 if	

Please choose the option Plan A or Plan B according to the instruction given above.

Game: 5

	Plan A			**Plan B**		
1.	250 if - 40 if			300 if -210 if		
2.	40 if - 40 if			300 if -210 if		
3.	10 if - 40 if			300 if -210 if		
4.	10 if - 40 if			300 if -160 if		
5.	10 if - 80 if			300 if -160 if		
6.	10 if - 80 if			300 if -140 if		
7.	10 if - 80 if			300 if -110 if		

References

Abebe, G. K., Bijman, J., Pascucci, S., & Omta, O. (2013). Adoption of improved potato varieties in Ethiopia: The role of agricultural knowledge and innovation system and smallholder farmers' quality assessment. *Agricultural Systems*, *122*, 22–32. https://doi.org/10.1016/j.agsy.2013.07.008

Adesina, A. A., & Zinnah, M. M. (1993). Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone. *Agricultural economics*, *9*(4), 297-311.

Ahsan, D. A. (2011). Farmers' motivations, risk perceptions and risk management strategies in a developing economy: Bangladesh experience. *Journal of Risk Research*, *14*(3), 325-349.

Akcaoz, H., & Ozkan, B. (2005). Determining risk sources and strategies among farmers of contrasting risk awareness: A case study for Cukurova region of Turkey. *Journal of Arid Environments*, *62*(4), 661–675. https://doi.org/10.1016/j.jaridenv.2005.01.018

Ali, S. Z., Sidhu, R. S., & Vatta, K. (2012). Effectiveness of Minimum Support Price Policy for Paddy in India with a Case Study of Punjab. *Agricultural Economics Research Review*, *25*(2), 231–242. https://doi.org/10.22004/ag.econ.137357

Andersen, S., Cox, J. C., Harrison, G. W., Lau, M. I., Rutström, E. E., & Sadiraj, V. (2018). Asset Integration and Attitudes toward Risk: Theory and Evidence. *The Review of Economics and Statistics*, *100*(5), 816–830. https://doi.org/10.1162/rest_a_00719

Andersen, S., Fountain, J., Harrison, G. W., Hole, A. R., & Rutström, E. E. (2012). *Inferring Beliefs as Subjectively Uncertain Probabilities*. 32.

Andersen, S., Fountain, J., Harrison, G. W., & Rutström, E. E. (2014). Estimating subjective probabilities. *Journal of Risk and Uncertainty*, *48*(3), 207–229. https://doi.org/10.1007/s11166-014-9194-z

Andersson, O., Holm, H. J., Tyran, J. R., & Wengström, E. (2016). Risk aversion relates to cognitive ability: Preferences or noise?. *Journal of the European Economic Association*, *14*(5), 1129-1154.

Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2006). Elicitation using multiple price list formats. *Experimental Economics*, *9*(4), 383–405. https://doi.org/10.1007/s10683-006-7055-6

Anderson, J. R., Dillon, J. L., & Hardaker, B. (1977). *Agricultural Decision Analysis* (No. 1114-2019–1852). AgEcon Search. https://doi.org/10.22004/ag.econ.288652

Antle, J. M. (1987). Econometric Estimation of Producers' Risk Attitudes. *American Journal of Agricultural Economics*, *69*(3), 509–522. https://doi.org/10.2307/1241687

Atanu, S., Love, H. A., & Schwart, R. (1994). Adoption of emerging technologies under output uncertainty. *American Journal of Agricultural Economics*, *76*(4), 836-846.

Asravor, R. K. (2019). Farmers' risk preference and the adoption of risk management strategies in Northern Ghana. *Journal of Environmental Planning and Management*, *62*(5), 881–900. https://doi.org/10.1080/09640568.2018.1452724

Babcock, B. A. (2015). Using Cumulative Prospect Theory to Explain Anomalous Crop Insurance Coverage Choice. *American Journal of Agricultural Economics*, *97*(5), 1371–1384. https://doi.org/10.1093/ajae/aav032

Bahta, Y. T., Willemse, B. J., & Grove, B. (2014). The role of agriculture in welfare, income distribution and economic development of the Free State Province of South Africa: A CGE approach. *Agrekon*, *53*(1), 46–74. https://doi.org/10.1080/03031853.2014.887905

Barham, B. L., Chavas, J.-P., Fitz, D., Salas, V. R., & Schechter, L. (2014). The roles of risk and ambiguity in technology adoption. *Journal of Economic Behavior & Organization*, *97*, 204–218. https://doi.org/10.1016/j.jebo.2013.06.014

Bardsley, P., & Harris, M. (1987). An Approach to the Econometric Estimation of Attitudes to Risk in Agriculture*. *Australian Journal of Agricultural Economics*, *31*(2), 112–126. https://doi.org/10.1111/j.1467-8489.1987.tb00669.x

Bar-Shira, Z., Just, R. E., & Zilberman, D. (1997). Estimation of farmers' risk attitude: An econometric approach. *Agricultural Economics*, *17*(2–3), 211–222. https://doi.org/10.1111/j.1574-0862.1997.tb00475.x

Bard, S. K., & Barry, P. J. (2000). Developing a scale for assessing risk attitudes of agricultural decision-makers. *The International Food and Agribusiness Management Review*, *3*(1), 9-25.

Becker, G. M., DeGroot, M. H., & Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behavioral science*, *9*(3), 226-232.

Belaid, A., & Miller, S. F. (1987). Measuring Farmers' Risk Attitudes: A Case Study of the Eastern High Plateau Region of Algeria. *Western Journal of Agricultural Economics*, *12*(2), 198–206. JSTOR. https://www.jstor.org/stable/40987870

Bellemare, M. F., Lee, Y. N., & Just, D. R. (2020). Producer Attitudes Toward Output Price Risk: Experimental Evidence from the Lab and from the Field. *American Journal of Agricultural Economics*, *102*(3), 806–825. https://doi.org/10.1002/ajae.12004

Benz, M., & Meier, S. (2008). Do people behave in experiments as in the field?—Evidence from donations. *Experimental Economics*, *11*(3), 268–281. https://doi.org/10.1007/s10683-007-9192-y

Bernard de Raymond, A., Alpha, A., Ben-Ari, T., Daviron, B., Nesme, T., & Tétart, G. (2021). Systemic risk and food security. Emerging trends and future avenues for research. *Global Food Security*, *29*, 100547. https://doi.org/10.1016/j.gfs.2021.100547

Bergfjord, O. J. (2009). Risk perception and risk management in Norwegian aquaculture. *Journal of Risk Research*, *12*(1), 91-104.

Binswanger, H. P. (1980). Attitudes toward Risk: Experimental Measurement in Rural India. *American Journal of Agricultural Economics*, *62*(3), 395. https://doi.org/10.2307/1240194

Binswanger, H. P. (1981). Attitudes toward risk: Theoretical implications of an experiment in rural India. *The Economic Journal*, *91*(364), 867-890.

Blavatskyy, P. (2013). Which decision theory? *Economics Letters*, *120*(1), 40–44. https://doi.org/10.1016/j.econlet.2013.03.039

Bocquého, G., Jacquet, F., & Reynaud, A. (2014). Expected utility or prospect theory maximizers? Assessing farmers' risk behavior from field-experiment data. *European Review of Agricultural Economics*, *41*(1), 135–172. https://doi.org/10.1093/erae/jbt006

Bonss, W. (2013). Risk. Dealing with Uncertainty in Modern Times. *Social Change Review*, *11*(1).

Bougherara, D., Gassmann, X., Piet, L., & Reynaud, A. (2017). Structural estimation of farmers' risk and ambiguity preferences: A field experiment. *European Review of Agricultural Economics*, *44*(5), 782–808. https://doi.org/10.1093/erae/jbx011

Bocquého, G., Jacquet, F., & Reynaud, A. (2014). Expected utility or prospect theory maximisers? Assessing farmers' risk behaviour from field-experiment data. *European Review of Agricultural Economics*, *41*(1), 135-172.

Bouchouicha, R., & Vieider, F. M. (2019). Growth, entrepreneurship, and risk-tolerance: a risk-income paradox. *Journal of Economic Growth*, *24*, 257-282

Cardenas, J. C., & Carpenter, J. (2013). Risk attitudes and economic well-being in Latin America. *Journal of Development Economics*, *103*, 52-61.

Bruner, D. M. (2011). Multiple switching behaviour in multiple price lists. *Applied Economics Letters*, *18*(5), 417-420.

Cerroni, S. (2020). Eliciting farmers' subjective probabilities, risk, and uncertainty preferences using contextualized field experiments. *Agricultural Economics*, *51*(5), 707–724. https://doi.org/10.1111/agec.12587

Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of economic behavior & organization*, *87*, 43-51.

Chavas, J.-P., & Holt, M. T. (1996). Economic Behavior Under Uncertainty: A Joint Analysis of Risk Preferences and Technology. *The Review of Economics and Statistics*, *78*(2), 329–335. JSTOR. https://doi.org/10.2307/2109935

Chavas, J.-P., Chambers, R. G., & Pope, R. D. (2010). Production Economics and Farm Management: A Century of Contributions. *American Journal of Agricultural Economics*, *92*(2), 356–375. JSTOR. https://www.jstor.org/stable/40647993

Chavas, J. P., & Nauges, C. (2020). Uncertainty, learning, and technology adoption in agriculture. *Applied Economic Perspectives and Policy*, *42*(1), 42-53.

Chhatre, A., Devalkar, S., & Seshadri, S. (2016). Crop diversification and risk management in Indian agriculture. *DECISION*, *43*(2), 167–179. https://doi.org/10.1007/s40622-016-0129-1

Chintapalli, P., & Tang, C. S. (2022). The implications of crop minimum support price in the presence of myopic and strategic farmers. *European Journal of Operational Research*, *300*(1), 336–349. https://doi.org/10.1016/j.ejor.2021.09.034

Coble, K. H., Knight, T. O., Patrick, G. F., & Baquet, A. E. (1999). Crop Producer Risk Management Survey: Report from the Understanding Farmer Risk Management Decision Making and Educational Needs Research Project (No. 1107-2016–91757). AgEcon Search. https://doi.org/10.22004/ag.econ.15805

Coble, K. H., Miller, J. C., Zuniga, M., & Heifner, R. (2004). The joint effect of government crop insurance and loan programmes on the demand for futures hedging. *European Review of Agricultural Economics*, *31*(3), 309–330. https://doi.org/10.1093/erae/31.3.309

Collins, A., Musser, W. N., & Mason, R. (1991). Prospect Theory and Risk Preferences of Oregon Seed Producers. *American Journal of Agricultural Economics*, *73*(2), 429–435. https://doi.org/10.2307/1242727 de Brauw, A., & Eozenou, P. (2014). Measuring risk attitudes among Mozambican farmers. *Journal of Development Economics*, *111*, 61–74. https://doi.org/10.1016/j.jdeveco.2014.08.002

Dessart, F. J., Barreiro-hurlé, J., & Bavel, R. V. (2019). Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review 46, 417–471.

Delavande, A., Giné, X., & McKenzie, D. (2011). Measuring subjective expectations in developing countries: A critical review and new evidence. *Journal of development economics*, *94*(2), 151-163

Di Girolamo, A., Harrison, G. W., Lau, M. I., & Swarthout, J. T. (2015). Subjective belief distributions and the characterization of economic literacy. *Journal of Behavioral and Experimental Economics*, *59*, 1–12. https://doi.org/10.1016/j.socec.2015.08.004

Diao, X., Hazell, P., & Thurlow, J. (2010). The Role of Agriculture in African Development. *World Development*, *38*(10), 1375–1383. https://doi.org/10.1016/j.worlddev.2009.06.011

Dillon, S., & Scandizz. (1978). *Risk Attitudes of Subsistence Farmers in Northeast Brazil*. https://scholar.google.com/scholar_url?url=https://academic.oup.com/ajae/article-pdf/60/3/425/110076/60-3 425.pdf&hl=en&sa=T&oi=ucasa&ct=usl&ei=HxukXpWIJJOGygSO5abABQ&scisig=AAGBfm10ZG2AnO82mz31dscXlo0bOy906Q

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2018). On the Relationship between Cognitive Ability and Risk Preference. *The Journal of Economic Perspectives*, *32*(2), 115–134. JSTOR. www.jstor.org/stable/26409427

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the european economic association*, *9*(3), 522-550.

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2010). Are risk aversion and impatience related to cognitive ability?. *American Economic Review*, *100*(3), 1238-1260.

Drichoutis, A. C., & Lusk, J. L. (2016). What can multiple price lists really tell us about risk preferences? *Journal of Risk and Uncertainty*, *53*(2), 89–106. https://doi.org/10.1007/s11166-016-9248-5

Duden, C., Mußhoff, O., & Offermann, F. (2023). Dealing with low-probability shocks: The role of selected heuristics in farmers' risk management decisions. *Agricultural Economics*, *54*(3), 382-399.

Elabed, Ghada & Carter, Michael R., 2013. "Basis Risk and Compound-Risk Aversion: Evidence from a WTP Experiment in Mali," 2013 Annual Meeting, August 4-6, 2013, Washington, D.C. 150353, Agricultural and Applied Economics Association.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The quarterly journal of economics*, *75*(4), 643-669.

Engle-Warnick, J., Escobal, J., & Laszlo, S. (2007). Ambiguity Aversion as a Predictor of Technology Choice: Experimental Evidence from Peru (SSRN Scholarly Paper ID 1077656). *Social Science Research Network.* https://doi.org/10.2139/ssrn.1077656

Eckel, C. C., & Grossman, P. J. (2003). Forecasting risk attitudes: An experimental study of actual and forecast risk attitudes of women and men. *Virginia Tech Department of Economics Working Paper*.

Feduzi, A., Runde, J., & Zappia, C. (2014). De Finetti on uncertainty. *Cambridge Journal of Economics*, *38*(1), 1–21. https://doi.org/10.1093/cje/bet054

Findlater, K. M., Satterfield, T., & Kandlikar, M. (2019). Farmers' risk-based decision making under pervasive uncertainty: cognitive thresholds and hazy hedging. *Risk Analysis*, *39*(8), 1755-1770.

Finger, R., Wüpper, D., & McCallum, C. (2023). The (in) stability of farmer risk preferences. *Journal of Agricultural Economics*, *74*(1), 155-167.

Flaten, O., Lien, G., Koesling, M., Valle, P. S., & Ebbesvik, M. (2005). Comparing risk perceptions and risk management in organic and conventional dairy farming: empirical results from Norway. *Livestock Production Science*, *95*(1-2), 11-25.

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annu. Rev. Econ.*, *2*(1), 395-424.

Fu, H., Zhang, Y., An, Y., Zhou, L., Peng, Y., Kong, R., & Turvey, C. G. (2022). Subjective and objective risk perceptions and the willingness to pay for agricultural insurance: Evidence from an in-the-field choice experiment in rural China. *The Geneva Risk and Insurance Review*, *47*(1), 98–121. https://doi.org/10.1057/s10713-021-00071-6

Galarza, F. (2009). *Choices under Risk in Rural Peru* [MPRA Paper]. https://mpra.ub.uni-muenchen.de/17708/

Gigerenzer, G., & Selten, R. (2001). Rethinking rationality. *Bounded rationality: The adaptive toolbox*, *1*, 12.

Glauber, J. W. (2013). The Growth of the Federal Crop Insurance Program, 1990—2011. *American Journal of Agricultural Economics*, *95*(2), 482–488. https://www.jstor.org/stable/23358421

Glauber, J. W., Collins, K. J., & Barry, P. J. (2002). Crop insurance, disaster assistance, and the role of the federal government in providing catastrophic risk protection. *Agricultural Finance Review*, *62*(2), 81–101. https://doi.org/10.1108/00214900280001131

Gonzalez-Ramirez, J., Arora, P., & Podesta, G. (2018). Using Insights from Prospect Theory to Enhance Sustainable Decision Making by Agribusinesses in Argentina. *Sustainability*, *10*(8), 2693. https://doi.org/10.3390/su10082693

Goodwin, B. K., & Schroeder, T. C. (1994). Human capital, producer education programs, and the adoption of forward-pricing methods. *American journal of agricultural economics*, *76*(4), 936-947.

Gonzalez, R., & Wu, G. (1999). On the Shape of the Probability Weighting Function. *Cognitive Psychology*, *38*(1), 129–166. https://doi.org/10.1006/cogp.1998.0710

Gonzalez-Ramirez, J., Arora, P., & Podesta, G. (2018). Using Insights from Prospect Theory to Enhance Sustainable Decision Making by Agribusinesses in Argentina. *Sustainability*, *10*(8), 2693. https://doi.org/10.3390/su1008269

Grisley, W., & Kellog, E. (1987). *Risk-Taking Preferences of Farmers in Northern Thailand: Measurements and Implications* (No. 968-2016–75379). Agricultural Economics: The Journal of the International Association of Agricultural Economists. https://doi.org/10.22004/ag.econ.172038

Greitemeyer, T., Kastenmüller, A., & Fischer, P. (2013). Romantic motives and risk-taking: An evolutionary approach. *Journal of Risk Research*, *16*(1), 19-38.

Gulati, A., Rajkhowa, P., & Sharma, P. (2017). Making Rapid Strides-Agriculture in Madhya Pradesh: Sources, Drivers, and Policy Lessons.

Gulati, A., Rajkhowa, P., Roy, R., & Sharma, P. (2021). Performance of Agriculture in Madhya Pradesh. *Revitalizing Indian Agriculture and Boosting Farmer Incomes*, 145-174.

Gupta, P., Khera, R., & Narayanan, S. (2021). Minimum Support Prices in India: Distilling the Facts. *Available at SSRN 3791859*.

Hardaker, J. B., & Lien, G. (2010). Probabilities for decision analysis in agriculture and rural resource economics: The need for a paradigm change. *Agricultural Systems*, *103*(6), 345–350. https://doi.org/10.1016/j.agsy.2010.01.001

Hardaker, J.B., Huirne, R.B.M., Anderson, J.R., 1997. Coping with Risk in Agriculture. CAB International, Wallingford.

Hansson, H., & Lagerkvist, C. J. (2012). Measuring farmers' preferences for risk: a domain-specific risk preference scale. *Journal of Risk Research*, *15*(7), 737-753.

Harrison, G. W., & List, J. A. (2004). Field experiments. *Journal of Economic literature*, *42*(4), 1009-1055.

Harrison, G. W., Humphrey, S. J., & Verschoor, A. (2010). Choice under Uncertainty: Evidence from Ethiopia, India and Uganda. *The Economic Journal*, *120*(543), 80–104. https://doi.org/10.1111/j.1468-0297.2009.02303.x

Harrison, G. W., & Rutström E. (2008). Risk Aversion in the Laboratory. In J. C. Cox & G. W. Harrison (Eds.), *Risk Aversion in Experiments* (Vol. 12, pp. 41–196). Emerald Group Publishing Limited. https://doi.org/10.1016/S0193-2306(08)00003-3

Harrison, G. W., List, J. A., & Towe, C. (2007). Naturally occurring preferences and exogenous laboratory experiments: A case study of risk aversion. *Econometrica*, *75*(2), 433-458.

Heinemann, F. (2005). Measuring Risk Aversion and the Wealth Effect. In *Discussion Paper Series of SFB/TR 15 Governance and the Efficiency of Economic Systems* (No. 156; Discussion Paper Series of SFB/TR 15 Governance and the Efficiency of Economic Systems). Free University of Berlin, Humboldt University of Berlin, University of Bonn, University of Mannheim, University of Munich. https://ideas.repec.org/p/trf/wpaper/156.html.

Hellerstein, D., Higgins, N., & Horowitz, J. (2013). The predictive power of risk preference measures for farming decisions. *European Review of Agricultural Economics*, *40*(5), 807–833. https://doi.org/10.1093/erae/jbs043

Hoda, A., Terway, P., 2015. Credit Policy for Agriculture in India - An Evaluation: Supporting Indian Farms the Smart Way: Rationalising Subsidies and Investments for Faster, Inclusive and Sustainable Growth. ICRIER Working Paper no. 302, Indian Council for Research on International Economic Relations, New Delhi.

Hoogendoorn, J. C., Audet-Bélanger, G., Böber, C., Donnet, M. L., Lweya, K. B., Malik, R. K., & Gildemacher, P. R. (2018). Maize seed systems in different agro-ecosystems; what works and what does not work for smallholder farmers. *Food Security*, *10*(4), 1089–1103. https://doi.org/10.1007/s12571-018-0825-0

Holt, C. A., & Laury, S. K. (2002). Risk Aversion and Incentive Effects. *American Economic Review*, *92*(5), 1644–1655. https://doi.org/10.1257/000282802762024700

Holden, S. T., Shiferaw, B., & Wik, M. (1998). Poverty, market imperfections and time preferences: of relevance for environmental policy?. *Environment and Development Economics*, *3*(1), 105-130.

Hu, M., Liu, Y., & Wang, W. (2019). Socially Beneficial Rationality: The Value of Strategic Farmers, Social Entrepreneurs, and For-Profit Firms in Crop Planting Decisions. *Management Science*, *65*(8), 3654–3672. https://doi.org/10.1287/mnsc.2018.3133

Hube, K. (1998). Investors must recall risk, investing's four letter word. *The Wall Street Journal Interactive Edition*.

Humphrey, S. J., & Verschoor, A. (2004a). Decision-making Under Risk among Small Farmers in East Uganda. *Journal of African Economies*, *13*(1), 44–101. https://doi.org/10.1093/jae/13.1.44

Humphrey, S. J., & Verschoor, A. (2004b). The probability weighting function: Experimental evidence from Uganda, India and Ethiopia. *Economics Letters*, *84*(3), 419–425. https://doi.org/10.1016/j.econlet.2004.02.015

Ihli, H. J., Gassner, A., & Musshoff, O. (2018). Experimental insights on the investment behavior of small-scale coffee farmers in central Uganda under risk and uncertainty. *Journal of Behavioral and Experimental Economics*, *75*, 31–44. https://doi.org/10.1016/j.socec.2018.04.011

Iyer, P., Bozzola, M., Hirsch, S., Meraner, M. & Finger, R. (2020) Measuring farmer risk preferences in Europe: a systematic review. Journal of Agricultural Economics, 71(1), 3–26.

Johansson-Stenman, O. (2006). A note on the risk behavior and death of homo economicus.

Just, D. R., & Lybbert, T. J. (2009). Risk Averters That Love Risk? Marginal Risk Aversion in Comparison to a Reference Gamble. *American Journal of Agricultural Economics*, *91*(3), 612–626. JSTOR. https://www.jstor.org/stable/20616223

Just, D. R., & Lybbert, T. J. (2012). A Generalized Measure of Marginal Risk Aversion: Experimental Evidence from India and Morocco. *American Journal of Agricultural Economics*, *94*(2), 444–450. JSTOR. https://www.jstor.org/stable/41331273

Just, D. R., & Peterson, H. H. (2010). Is Expected Utility Theory Applicable? A Revealed Preference Test. *American Journal of Agricultural Economics*, *92*(1), 16–27. https://doi.org/10.1093/ajae/aap015

Just, R. E. (2003). Risk research in agricultural economics: Opportunities and challenges for the next twenty-five years. *Agricultural Systems*, *75*(2), 123–159. https://doi.org/10.1016/S0308-521X(02)00063-X

Just, R. E., & Pope, R. D. (2003). Agricultural Risk Analysis: Adequacy of Models, Data, and Issues. *American Journal of Agricultural Economics*, *85*(5), 1249–1256. https://doi.org/10.1111/j.0092-5853.2003.00538.x

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–291. JSTOR. https://doi.org/10.2307/1914185

Kapoor, S., & Kapoor, S. (2022). Effectiveness of non-farm diversification on rural household income–evidence and policy implications from India. *International Journal of Development Issues*, *21*(1), 1-23.

Karni, E. (1993). A Definition of Subjective Probabilities with State-Dependent Preferences. *Econometrica*, *61*(1), 187–198. https://doi.org/10.2307/2951783

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, *129*(2), 597-652.

Klibanoff, P., Marinacci, M., & Mukerji, S. (2005). A smooth model of decision making under ambiguity. *Econometrica*, *73*(6), 1849-1892.

Knight, T. O., & Coble, K. H. (1997). Survey of U.S. Multiple Peril Crop Insurance Literature Since 1980. *Applied Economic Perspectives and Policy*, *19*(1), 128–156. https://doi.org/10.2307/1349683

Kunreuther, H., Heal, G., Allen, M., Edenhofer, O., Field, C. B., & Yohe, G. (2013). Risk management and climate change. *Nature Climate Change*, *3*(5), 447–450. https://doi.org/10.1038/nclimate1740

LeRoy, S. F., & Singell Jr, L. D. (1987). Knight on risk and uncertainty. *Journal of political economy*, *95*(2), 394-406.

Leppälä, J., Rautiainen, R., & Kauranen, I. (Eds.). (2015). Analysis of risk management tools applicable in managing farm risks: A literature review. *International Journal of Agricultural Management*. https://doi.org/10.22004/ag.econ.262368

Liebenehm, S., & Waibel, H. (2014). Simultaneous Estimation of Risk and Time Preferences among Small-scale Cattle Farmers in West Africa. *American Journal of Agricultural Economics*, *96*(5), 1420–1438. https://doi.org/10.1093/ajae/aau056

Lichtenstein, S., & Slovic, P. (1971). Reversals of preference between bids and choices in gambling decisions. *Journal of experimental psychology*, *89*(1), 46.

Liu, E. M. (2012). Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China. *The Review of Economics and Statistics*, *95*(4), 1386–1403. https://doi.org/10.1162/REST_a_00295

Liu, E. M., & Huang, J. (2013). Risk preferences and pesticide use by cotton farmers in China. *Journal of Development Economics*, *103*, 202–215. https://doi.org/10.1016/j.jdeveco.2012.12.005

Loizou, E., Karelakis, C., Galanopoulos, K., & Mattas, K. (2019). The role of agriculture as a development tool for a regional economy. *Agricultural Systems*, *173*, 482–490. https://doi.org/10.1016/j.agsy.2019.04.002

Lowenberg-DeBoer, J. (2015). The Precision Agriculture Revolution: Making the Modern Farmer. *Foreign Affairs*, *94*(3), 105–112. https://www.jstor.org/stable/24483669

Lucas, M. P., & Pabuayon, I. M. (2011). *Risk Perceptions, Attitudes, and Influential Factors of Rainfed Lowland Rice Farmers in Ilocos Norte, Philippines*. Asian Journal of Agriculture and Development. https://doi.org/10.22004/ag.econ.199327

Lybbert, T. J. (2006). Indian farmers' valuation of yield distributions: Will poor farmers value 'pro-poor' seeds? *Food Policy*, *31*(5), 415–441. https://doi.org/10.1016/j.foodpol.2005.11.001

Lybbert, T. J., & Bell, A. (2010). Stochastic benefit streams, learning, and technology diffusion: why drought tolerance is not the new Bt. https://mospace.umsystem.edu/xmlui/handle/10355/7074

Maart-Noelck, S. C., & Musshoff, O. (2013). Investing Today or Tomorrow? An Experimental Approach to Farmers' Decision Behaviour. *Journal of Agricultural Economics*, *64*(2), 295–318. https://doi.org/10.1111/j.1477-9552.2012.00371.x

Magruder, J. R. (2018). An assessment of experimental evidence on agricultural technology adoption in developing countries. *Annual Review of Resource Economics*, *10*, 299-316.

Marra, M., Pannell, D. J., & Ghadim, A. A. (2003). The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve? *Agricultural systems*, *75*(2-3), 215-234.

Machina, M. J. (1982). “Expected Utility” Analysis without the Independence Axiom. *Econometrica*, *50*(2), 277–323. JSTOR. https://doi.org/10.2307/1912631

MacCrimmon, K. R., & Wehrung, D. A. (1986). Assessing risk propensity. In *Recent developments in the foundations of utility and risk theory* (pp. 291-309). Springer, Dordrecht

Maertens, A., Chari, A. V., & Just, D. R. (2014). Why Farmers Sometimes Love Risks: Evidence from India. *Economic Development and Cultural Change*, *62*(2), 239–274. https://doi.org/10.1086/674028

Manski, C. F., & Lerman, S. R. (1977). The Estimation of Choice Probabilities from Choice Based Samples. *Econometrica*, *45*(8), 1977–1988. JSTOR. https://doi.org/10.2307/1914121

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013). Poverty Impedes Cognitive Function. *Science*, *341*(6149), 976–980. https://doi.org/10.1126/science.1238041

Markowitz, H. (1952). The utility of wealth. *Journal of political Economy*, *60*(2), 151-158.

Menapace, L., Colson, G., & Raffaelli, R. (2013). Risk aversion, subjective beliefs, and farmer risk management strategies. *American Journal of Agricultural Economics*, *95*(2), 384-389.

Menapace, L., Colson, G., & Raffaelli, R. (2016). A comparison of hypothetical risk attitude elicitation instruments for explaining farmer crop insurance purchases. *European Review of Agricultural Economics*, *43*(1), 113-135.

Meraner, M., & Finger, R. (2019). Risk perceptions, preferences and management strategies: evidence from a case study using German livestock farmers. *Journal of Risk Research*, *22*(1), 110-135.

Mittal, S., & Hariharan, V. K. (2016). Crop Diversification by Agro-climatic Zones of India-Trends and Drivers. *Indian Journal of Economics and Development*, *12*(1), 123. https://doi.org/10.5958/2322-0430.2016.00014.7

Miyata, S. (2003). Household’s risk attitudes in Indonesian villages. *Applied Economics*, *35*(5), 573–583. https://doi.org/10.1080/0003684022000020823

Moschini, G., & Hennessy, D. A. (2001). Chapter 2 Uncertainty, risk aversion, and risk management for agricultural producers. In *Handbook of Agricultural Economics* (Vol. 1, pp. 87–153). Elsevier. https://doi.org/10.1016/S1574-0072(01)10005-8

Moscardi, E., & de Janvry, A. (1977). Attitudes toward Risk among Peasants: An Econometric Approach. *American Journal of Agricultural Economics*, *59*(4), 710. https://doi.org/10.2307/1239398

Moser, S., & Mußhoff, O. (2017, June 1). *Comparing the Use of Risk influencing Production Inputs and Experimentally Measured Risk Attitude: Do the Decisions of Indonesian Small scale Rubber Farmers Match?* (No. 670-2020–980). German Journal of Agricultural Economics. https://doi.org/10.22004/ag.econ.303544

Moser, S. (2015). Analysing smallholders behaviour on Sumatra: An ex ante policy analysis and investigation of experiments external validity under consideration of risk.

Mosley, P., & Verschoor, A. (2005). Risk Attitudes and the 'Vicious Circle of Poverty.' *The European Journal of Development Research*, *17*(1), 59–88. https://doi.org/10.1080/09578810500066548

Narayanan, S. (2016). The productivity of agricultural credit in India. *Agricultural Economics*, *47*(4), 399-409.

Nguyen, Q. (2011). Does nurture matter: Theory and experimental investigation on the effect of working environment on risk and time preferences. *Journal of Risk and Uncertainty*, *43*(3), 245–270. https://doi.org/10.1007/s11166-011-9130-4

Nguyen, Q., & Leung, P. (2009). Do Fishermen Have Different Attitudes Toward Risk? An Application of Prospect Theory to the Study of Vietnamese Fishermen. *Journal of Agricultural and Resource Economics*, *34*(3), 518–538. JSTOR. https://www.jstor.org/stable/41548431

NGUYEN, Q., & LEUNG, P. (2010). How nurture can shape preferences: An experimental study on risk preferences of Vietnamese fishers. *Environment and Development Economics*, *15*(5), 609–631. https://www.jstor.org/stable/44379343

Norris, P. E., & Kramer, R. A. (1990). *The Elicitation of Subjective Probabilities with Applications in Agricultural Economics* (No. 430-2016–31574). Review of Marketing and Agricultural Economics. https://doi.org/10.22004/ag.econ.12253

Ouattara, P. D., Kouassi, E., Egbendéwé, A. Y. G., & Akinkugbe, O. (2019). Risk aversion and land allocation between annual and perennial crops in semisubsistence farming: A stochastic optimization approach. *Agricultural Economics*, *50*(3), 329–339. https://doi.org/10.1111/agec.12487

Pannell, D. J., Malcolm, B., & Kingwell, R. S. (2000). Are we risking too much? Perspectives on risk in farm modeling. *Agricultural Economics*, *23*(1), 69–78. https://doi.org/10.1111/j.1574-0862.2000.tb00084.x

Pease, J. W., Wade, E. W., Skees, J. S., & Shrestha, C. M. (1993). Comparisons between Subjective and Statistical Forecasts of Crop Yields. *Applied Economic Perspectives and Policy*, *15*(2), 339–350. https://doi.org/10.2307/1349453

Pennings, J. M., & Leuthold, R. M. (2000). The role of farmers' behavioral attitudes and heterogeneity in futures contracts usage. *American journal of agricultural economics*, *82*(4), 908-919.

Pennings, J. M., & Garcia, P. (2001). Measuring producers' risk preferences: A global risk-attitude construct. *American journal of agricultural economics*, *83*(4), 993-1009.

Prelec, D. (1998). The probability weighting function. *Econometrica*, 497-527.

Quiggin, J. (1981). Risk perception and the analysis of risk attitudes. *Australian Journal of Agricultural Economics*, *25*(2), 160-169.

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization*, *3*(4), 323–343. https://doi.org/10.1016/0167-2681(82)90008-7

Quiggin, J. (1991). Comparative statics for rank-dependent expected utility theory. *Journal of Risk and Uncertainty*, *4*(4), 339–350. https://doi.org/10.1007/BF00056160

Quinn, C. H., Huby, M., Kiwasila, H., & Lovett, J. C. (2003). Local perceptions of risk to livelihood in semi-arid Tanzania. *Journal of Environmental Management*, *68*(2), 111-119.

Rabin, M. (2000). *Diminishing Marginal Utility of Wealth Cannot Explain Risk Aversion*. https://escholarship.org/uc/item/61d7b4pg

Reynaud, A., & Couture, S. (2012). Stability of risk preference measures: Results from a field experiment on French farmers. *Theory and Decision*, *73*(2), 203–221. https://doi.org/10.1007/s11238-012-9296-5

Roe, B. E. (2015). The risk attitudes of US farmers. *Applied Economic Perspectives and Policy*, *37*(4), 553-574.

Ross, N., Santos, P., & Capon, T. (2012). *Risk, ambiguity and the adoption of new technologies: Experimental evidence from a developing economy*. AgEcon Search. https://doi.org/10.22004/ag.econ.126492

Rothschild, M., & Stiglitz, J. E. (1971). Increasing risk II: Its economic consequences. *Journal of Economic Theory*, *3*(1), 66–84. https://doi.org/10.1016/0022-0531(71)90034-2

Saha, A. (1993). Expo-power utility: a ‘flexible’form for absolute and relative risk aversion. *American Journal of Agricultural Economics*, *75*(4), 905-913.

Schaak, H., Buchholz, M., Hermann, D., Holst, G. S., & Mußhoff, O. (2017). *The Predictive Power Of Experimental Risk Attitude Measures For Farm Diversification* 12. *Schriften der Gesellschaft für Wirtschafts- und Sozialwissenschaften des Landbaues e.V., Bd. 52, 87 – 97*

Schechter, L. (2007). Risk aversion and expected-utility theory: A calibration exercise. *Journal of Risk and Uncertainty*, *35*(1), 67–76. https://doi.org/10.1007/s11166-007-9017-6

Senapati, A. K. (2020). Evaluation of risk preferences and coping strategies to manage with various agricultural risks: Evidence from India. *Heliyon*, *6*(3), e03503. https://doi.org/10.1016/j.heliyon.2020.e03503

Serra, T., Goodwin, B. K., & Featherstone, A. M. (2003). Modeling changes in the U.S. demand for crop insurance during the 1990s. *Agricultural Finance Review*, *63*(2), 109–125. https://doi.org/10.1108/00215030380001144

Shaik, S., Coble, K. H., Knight, T. O., Baquet, A. E., & Patrick, G. F. (2008). Crop Revenue and Yield Insurance Demand: A Subjective Probability Approach. *Journal of Agricultural and Applied Economics*, *40*(3), 757–766. https://doi.org/10.1017/S1074070800002303

Simon, H. A. (1966). Theories of decision-making in economics and behavioural science. In *Surveys of economic theory* (pp. 1-28). Palgrave Macmillan, London

Sitkin, S. B., & Pablo, A. L. (1992). Reconceptualizing the determinants of risk behavior. *Academy of management review*, *17*(1), 9-38

Smith, J., & Mandac, A. M. (1995). Subjective versus Objective Yield Distributions as Measures of Production Risk. *American Journal of Agricultural Economics*, *77*(1), 152–161. https://doi.org/10.2307/1243897

Sjöberg, L. (1980). The risks of risk analysis. *Acta Psychologica*, *45*(1-3), 301-321.

Sj ̈oberg L, Moen B & Rundmo, T. (2004). Explaining Risk Perception: An Evaluation of the Psychometric Paradigm in Risk Perception Research. *Trondheim*: *Norwegian University of Science and Technology, Department of Psychology*.

Slovic, P., Fischhoff, B., & Lichtenstein, S. (1982). Why study risk perception?. *Risk analysis*, *2*(2), 83-93.

Spielman, D. J., & Smale, M. (2017). *Policy Options to Accelerate Variety Change Among Smallholder Farmers in South Asia and Africa South of the Sahara* (SSRN Scholarly Paper ID 3029612). Social Science Research Network. https://papers.ssrn.com/abstract=3029612

Starmer, C. (2000). Developments in Non-expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk. *Journal of Economic Literature*, *38*(2), 332–382. https://doi.org/10.1257/jel.38.2.332

Suppes, P. (2006). Ramsey's Psychological Theory of Belief. In M. C. Galavotti (Ed.), *Cambridge and Vienna: Frank P. Ramsey and the Vienna Circle* (pp. 35–53). Springer Netherlands. https://doi.org/10.1007/1-4020-4101-2_4

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review*, *100*(1), 557–571. https://doi.org/10.1257/aer.100.1.557

Thaler, R. H., & Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth, and happiness*. Penguin.

Tonsor, G. T. (2018). Producer Decision Making under Uncertainty: Role of Past Experiences and Question Framing. *American Journal of Agricultural Economics*, *100*(4), 1120–1135. https://doi.org/10.1093/ajae/aay034

Tripathi, A. K. (Ed.). (2012). Agricultural Price Policy, Output, and FarmProfitability—Examining Linkages during Post-Reform Period in India. *Asian Journal of Agriculture and Development*. https://doi.org/10.22004/ag.econ.199109

Turvey, C. G., Gao, X., Nie, R., Wang, L., & Kong, R. (2013). Subjective Risks, Objective Risks and the Crop Insurance Problem in Rural China. *The Geneva Papers on Risk and Insurance - Issues and Practice*, *38*(3), 612–633. https://doi.org/10.1057/gpp.2012.42

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323. https://doi.org/10.1007/BF00122574

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, *185*(4157), 1124-1131.

Ullah, R., Shivakoti, G. P., Kamran, A., & Zulfiqar, F. (2016). Farmers versus nature: Managing disaster risks at farm level. *Natural Hazards*, *82*(3), 1931–1945. https://doi.org/10.1007/s11069-016-2278-0

Ullah, R., Shivakoti, G. P., Zulfiqar, F., & Kamran, M. A. (2016). Farm risks and uncertainties: Sources, impacts and management. *Outlook on Agriculture*, *45*(3), 199–205. https://doi.org/10.1177/0030727016665440

Ullah, R., Jourdain, D., Shivakoti, G. P., & Dhakal, S. (2015). Managing catastrophic risks in agriculture: Simultaneous adoption of diversification and precautionary savings. *International Journal of Disaster Risk Reduction*, *12*, 268-277.

van Winsen, F., de Mey, Y., Lauwers, L., Van Passel, S., Vancauteren, M., & Wauters, E. (2016). Determinants of risk behaviour: effects of perceived risks and risk attitude on farmer's adoption of risk management strategies. *Journal of Risk Research*, *19*(1), 56-78.

Vieider, F. M., Martinsson, P., Nam, P. K., & Truong, N. (2019). Risk preferences and development revisited. *Theory and Decision*, *86*(1), 1–21. https://doi.org/10.1007/s11238-018-9674-8

Villacis, A. H., Alwang, J. R., & Barrera, V. (2021). Linking risk preferences and risk perceptions of climate change: A prospect theory approach. *Agricultural Economics*, *52*(5), 863–877. https://doi.org/10.1111/agec.12659

Vollmer, E., Hermann, D., & Mußhoff, O. (2017). Is the risk attitude measured with the Holt and Laury task reflected in farmers' production risk? *European Review of Agricultural Economics*, *44*(3), 399–424. https://doi.org/10.1093/erae/jbx004

Ward, P. S., & Singh, V. (2015). Using Field Experiments to Elicit Risk and Ambiguity Preferences: Behavioural Factors and the Adoption of New Agricultural Technologies in Rural India. *The Journal of Development Studies*, *51*(6), 707–724. https://doi.org/10.1080/00220388.2014.989996

Warnick, J. C. E., Escobal, J., & Laszlo, S. C. (2011). Ambiguity aversion and portfolio choice in small-scale Peruvian farming. *The BE Journal of Economic Analysis & Policy*, *11*(1).

Weber, E. U., & Milliman, R. A. (1997). Perceived risk attitudes: Relating risk perception to risky choice. *Management science*, *43*(2), 123-144.

Wik *, M., Kebede, T. A., Bergland, O., & Holden, S. T. (2004). On the measurement of risk aversion from experimental data. *Applied Economics*, *36*(21), 2443–2451. https://doi.org/10.1080/0003684042000280580

Willock, J., Deary, I. J., McGregor, M. M., Sutherland, A., Edwards-Jones, G., Morgan, O., ... & Austin, E. (1999). Farmers' attitudes, objectives, behaviors, and personality traits: The Edinburgh study of decision making on farms. *Journal of Vocational Behavior*, *54*(1), 5-36.

Yamano, T., Rajendran, S., & Malabayabas, M. L. (2015). Farmers' self-perception toward agricultural technology adoption: evidence on adoption of submergence-tolerant rice in Eastern India. *Journal of Social and Economic Development*, *17*, 260-274.

Yesuf, M., & Bluffstone, R. A. (2009). Poverty, risk aversion, and path dependence in low-income countries: Experimental evidence from Ethiopia. *American Journal of Agricultural Economics*, *91*(4), 1022-1037.

Zhao, S., & Yue, C. (2020). Risk preferences of commodity crop producers and specialty crop producers: An application of prospect theory. *Agricultural Economics*, *51*(3), 359–372. https://doi.org/10.1111/agec.12559

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Scope of Behavioral Economics in Agricultural Decision-Making

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Abstract: ***This paper provides a general overview of behavioral economics in agricultural decision-making. In the first part, we discussed how behavioral economics complemented and provided new insights, a different perspective of the understanding of modeling agricultural decisions in ongoing argument of deviation of profit maximization behavior among farmers. Next, farmers' behavioral responses to risk and uncertainty inan inherent risky environment in agricultural activities, in which an alternative approach provides better insightsfor understanding risky decisions. We have also discussed the important behavioral finding of bounded rationality, i. e., cognitive limitation and biases-a significant characteristic that affect the farmers' decisions; finally, we discussed the role of experimental methods in agricultural economics that significantly helps in better policy analysis through behavioral economics.***

Keywords: Behavioral Economics**,** Decision-Making, Agricultural Economics, Risk behavior, Experimental Method

1. Introduction

Changing consumption patterns and increasing food demand puts more pressure on available resources. It causes an intensive use of resources and gives rise to the over-exploitation of our planet, which is already on the verge of a critical stage. In addition, the consequence of growing climate concerns and pets and disease worsens things and culminates in a fragile and risky decision-making environment. These challenges make policymakers' and farmers' decisions more critical in designing agricultural practices, fulfilling the current generations' desires without compromising future opportunities. It becomes even more complex while including the priorities for establishing sustainable agricultural practices established by the Sustainable Development Goals of the 2030 Agenda of the United Nations. All these challenges intervene with each other and make it too complex to model and understand the agricultural decision.

Various studies raised concerns about understanding and modeling the process and consequences of farming decisions. Willock (1999) highlighted the importance of personality, attitude, and the role of cognition in setting objectives in farm decision-making and found significant differences in goal settings. Schwarze et al. (2014) also concluded in an experimental setting that farmers are not utility maximizers. Further, Appel &Balmann (2019) revealed important behavioral characteristics of farmers who were more resilient in difficult situations and mostly followed a path-dependent strategy. This study also found that cognition was an important determinant of success. In some recent studies, scholars have made an attempt, an alternative views, a behavioral and psychological method to explain various agricultural phenomena by designing effective food and production policies with set goals (Edwards-Jones, 2006; Just, 2006; Lusk &McCluskey, 2018: Liu et al., 2014;).

This study explores the scope of behavioral economics, economic psychology, and decision theory in agricultural making. Recent developments in behavioral economics, i. e., anchoring, biases, intuition, cognition, loss aversion, and nudging, are common practices in decision-making. All these terms have been found to be more prevalent in decision-making. This study aims to analyze how different behavioral approaches explain complex agricultural decisions under different conditions. Therefore, in section two, we have discussed the significance of behavioral factors in agricultural decision modeling. In section three, we have discussed the insights of risky behavior through the lens of behavioral economics in agricultural decisions. In section four, we have discussed how cognitive biases significantly influence farmers' decision-making. In section five, we have discussed the role of experimental methods in behavioral and agricultural decision-making. Finally, in section six, we summarize our arguments in the light of the above discussion.

2. Modeling Agricultural decisions

The fundamental assumption of strong rationality behavior is that profit is the sole driver of decision-making. With this underlying assumption that farmers can perfectly account for each criterion, i. e identifying all alternatives, the best possible crops that ensure the optimal production of the best use of soil, existing government policy and market support, and other costs, etc. But behavioral economists emphasized individual capabilities' limitations and observed that this assumption could not hold in all cases. Willock (1999) explained behavioral factors, i. e., intuition, cognition, and biases, are relevant in modeling farmers' decisions, and they intervene as mediating variables between dependent and independent variables.

A study examining the optimal decisions among Dutch farmers found that farmers were unable to reach their optimum choices to account for the implication of animal health; cost-benefit analysis on animal health expenditure and its returns (Huijps et al., 2010). They were not adopting compliance with the given expert advice. This implies that farmers do not always implement best management

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Determinants of Risk Behavior among Poor Farmers

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Abstract: Risk behavior is crucial among poor in developing countries, their daily risk and probability decisions matter for their livelihood and overall well-being in the long run. Risky choices varied with decision-makers' characteristics and their economic capability. We investigated farmer risk behavior in Madhya Pradesh, India using a Holt-Laury experimental procedure to examine the determinants of risk behavior. We found that individual characteristics are more important in determining risk behavior among poor rather different wealth indicators.

Keywords: Risk Attitude**,** Holt-Laury Method, Experimental Economics

JEL Classification Number: C91 D81

1. Introduction

Agricultural activity is inherently a risky business. Poor farmers are generally more vulnerable in developing countries with limited options to mitigate risk and uncertainty. Farmers in the developing countries, in general, have more risk exposure in the farm activities. Resource constraints and a lack of information about prospects led to higher risk. It causes to lag behind in managing risks and often make sub-optimal choices in all agricultural decisions.

Varied risk behavior has been observed among farmers' given resource constraints and sets of information. Risk attitude is generally assumed to determine risk behavior in decision-making (Pennings and Garcia, 2001; Weber and Milliman, 1997; Willock et al., 1990). Risk attitude is sometimes referred to as a risk preference- individual response toward risk-taking in real-life decisions. Farmers' risk preferences vary from extreme risk aversion behavior to risk-seeking behavior. Although, most of the studies generally assumed that farmers' behavior is naturally risk-averse. But some studies have also found that farmers are sometimes keen to take more risk-a risk-seeking behavior (Maertens et al. 2014).

Given the importance of risk management, it is crucial to understand the farmer risk behavior for a better risk management strategy and various policy designs. For an effective policy

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by Raghavendra Kushawaha

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