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Risks in Food Systems: Understanding how Risk Affects Small-Scale Producer's Decision-making

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Key messages

- The IPCC defines risk as "the potential for adverse consequences for human or ecological systems". In food systems, risks emerge from the interaction of climatic, economic, and institutional hazards with differential exposure and vulnerability across actors.
- Small-scale producers (SSPs), as key actors in food systems, face multiple risks. They make farming decisions based on how they perceive these risks, shaped by their own risk tolerance and assessment of dread, familiarity, and other characteristics of the hazard, and that can diverge from actuarial risk.
- This technical brief discusses SSP decision-making in food systems, in the context of IPCC defined risk, and illustrates how risk perceptions and risk attitudes are integrated into CRIFS' research agenda on SSP technology adoption.

1. Background[1]

Supporting small-scale agriculture in an environment of increasing climate and market volatility, conflicts, and other livelihood uncertainties requires a clear definition of risk and an analytical framework for understanding how producers gather, process, and act on information about risk scenarios and adaptation options. A large literature documents the types of risks faced by small-scale producers (SSPs), defined as farmers with small land and/or livestock holdings (EPAR, 2025a). These SSPs are key actors of food systems in low-and-middle income countries (EPAR, 2025b) and face a variety of risks, including hard-to-predict climate shocks and prices. Many analyses of agricultural technology adoption implicitly assume that adoption follows once technologies are available that have the potential to enhance outcomes such as productivity or income.

However, this approach overlooks that SSPs evaluate new technologies by comparing their expected returns against those of previously available technologies, in a process arguably shaped by risk perceptions and risk attitudes. Risk perceptions are defined as the process of collecting, selecting, and interpreting signals about uncertain outcomes (Wachinger et al., 2013). While risk perceptions form beliefs about the likelihood and adversity of uncertain events, risk attitudes direct decision-making under uncertainty given those beliefs. Risk attitudes represent one's more innate tendency to prefer a risky option or a safe option of an equal or lower expected value (Hsee and Weber, 1998; Weber, 2001). Building on the IPCC definition of risk and these

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Established in 2008, EPAR uses an innovative student-faculty team model to provide rigorous, applied research and analysis to international development stakeholders.

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definitions of risk perceptions and risk attitudes, this brief discusses how risk shapes SSP technology adoption decisions. It proposes a simple seed choice model under drought risk from which testable hypotheses on risk perceptions and risk attitudes are derived and provides numerical examples that illustrate how each can deter adoption of new technologies even when the new technologies' expected returns exceed those of traditional alternatives. The brief also discusses how behavioral factors are integrated into a research agenda on climate risks in food systems and SSP technology adoption.

2. Defining and characterizing risk in food systems

The IPCC Sixth Assessment Report define risk as *"the potential for adverse consequences for human or ecological systems"* (Reisinger et al., 2020). The IPCC report focuses on climate risk, which emerges from the combination of hazard, exposure, and vulnerability.

- Hazard refers to the potential occurrence of a physical event that may cause negative consequences to human health, property, or ecosystems and environmental resources.
- Exposure is the presence of people or ecosystems and assets that have a probability of experiencing an adverse event.
- Vulnerability captures the propensity to experience an adverse event and encompasses both the ability to withstand an impact and the ability to cope with its aftermath.

Under the IPCC framework, a physical event constitutes climate risk only if it is linked to potential adverse consequences for human or ecological systems. For example, the potential of delayed rains is not itself a risk. However, the potential of rain that could reduce crop yields (hazard) creates a risk for food security when affecting SSPs who practice rainfed farming (exposure) and lack irrigation or alternative income sources (vulnerability).

Although the IPCC risk framework focuses primarily on climate risks, it is highly relevant for analyzing other sources of risk in food systems. CRIFS adopts a broad approach to risk, following Komarek et al. (2020)'s useful classification of types and sources of risks in agriculture. CRIFS considers the following risks:

- Production risks stemming from natural growth processes of crops and livestock (e.g., adverse climate, pests, and diseases, adverse changes to soil quality, etc.).
- Market risks due to uncertainty with prices, costs, and market access (e.g., untimely input availability, unpredictable quality of inputs, input and output price volatility, limited output market access, etc.).
- Institutional risks related to unpredictable changes in policies and regulations that affect agriculture (e.g., unpredictable changes in tariffs or subsidies policies, regulations affecting SSPs, etc.).
- Personal risks such as human health or personal relationship that affect the farm or farm household (e.g., adverse health outcomes and food security of household members).
- Financial risks caused by variability in cash flow due to fixed credit use obligation, often stemming from changes in interest rates or credit conditions (e.g., changes in credit availability or credit conditions that generate liquidity constraints for input purchases).

These risks often interact with and compound each other. CRIFS is particularly interested in how climate risks generate and amplify other agricultural risks. For example, drought-caused harvest failure may reduce one's own-consumption of the harvest and income from harvest sales, thereby increasing the personal risk of food insecurity. If limited harvest sales compromised the ability to finance previous loans, the financial risk of not obtaining future credit may increase. While the boundaries between these sources and types of risk vary by context, agents, and outcomes of interest, they provide a useful basis to study agriculture in risky environments. For the remainder of this brief, we focus on illustrating SSP's decision-making under climate risks.

3. Risk perceptions and attitudes in agricultural decision-making

Because there is no single accepted formal axiomatic model of decision-making under uncertainty, we organize the analysis of SSP technology adoption decision-making under risk on the conceptual framework shown in Figure 1. That framework begins with enabling preconditions shaped by institutional and market systems—such as access to inputs, credit, labor, and information—which determine whether technology is available and accessible. Conditional on availability, accessibility, and awareness, adoption decisions are framed as risk-return calculations shaped by multiple factors, including expected returns, and, critically, risk perceptions and risk attitudes.[2] Our framework is consistent with the risk-value framework in Figner and Weber (2015) in which decision-making is a function of the decision-maker's perceived riskiness and return of different courses of action and willingness to trade off perceived risk for return.

Risk perceptions can be described by two-dimensional risk priority matrices that assign scores to events based on the hazard's <u>perceived likelihood</u> and <u>perceived adversity</u> (Elrick-Barr et al., 2015). We propose that each dimension is associated with widely used constructs from the risk analysis literature: perceived likelihood with heuristics, and perceived adversity with qualitative dimensions of the hazard. On the one hand, heuristics consist of reducing the complex task of assessing probabilities to simpler judgmental operations (Tversky and Kahneman, 1974) which can introduce decision-biases.[3] On the other, qualitative characteristics of the hazard from psychometric research reflect the extent to which an event is associated with dread (e.g., cannot be easily observed or controlled, leads to salient fatalities, is the consequence of involuntary exposure, and is catastrophic in magnitude) or unknown (e.g., novel, incompletely understood, and temporally or spatially distant) regardless of perceived or actuarial (i.e., expert-derived) probabilities (Slovic, 1987; Siegrist and Arvai, 2020).[4]

Risk attitudes concern not how risks are perceived but how, given beliefs about hazard probabilities and adversity, choices are made. For example, once a farmer's beliefs are formed about the probability of drought and the payoffs associated with traditional versus drought-resistant seeds, the seed chosen ex-ante is determined by risk attitudes. Risk attitudes are relatively stable personality traits (Weber, 2001) that represent the willingness to trade off perceived risk for return (Figner and Weber, 2015; Hsee and Weber, 1998). In expected utility theory, a decision-maker who consistently prefers a certain return over a lottery of equal expected value is said to be risk averse. There is a longstanding literature criticizing rational choice models of choice under uncertainty, including Bernoulli "utility" and other expected utility theories (Tversky, 1975). In a synthesis of decision-making models under uncertainty from economics, psychology and biology, Höppner (2026, p.304) notes that expected utility theory "clashes with real-world behavior: Individuals often conflate

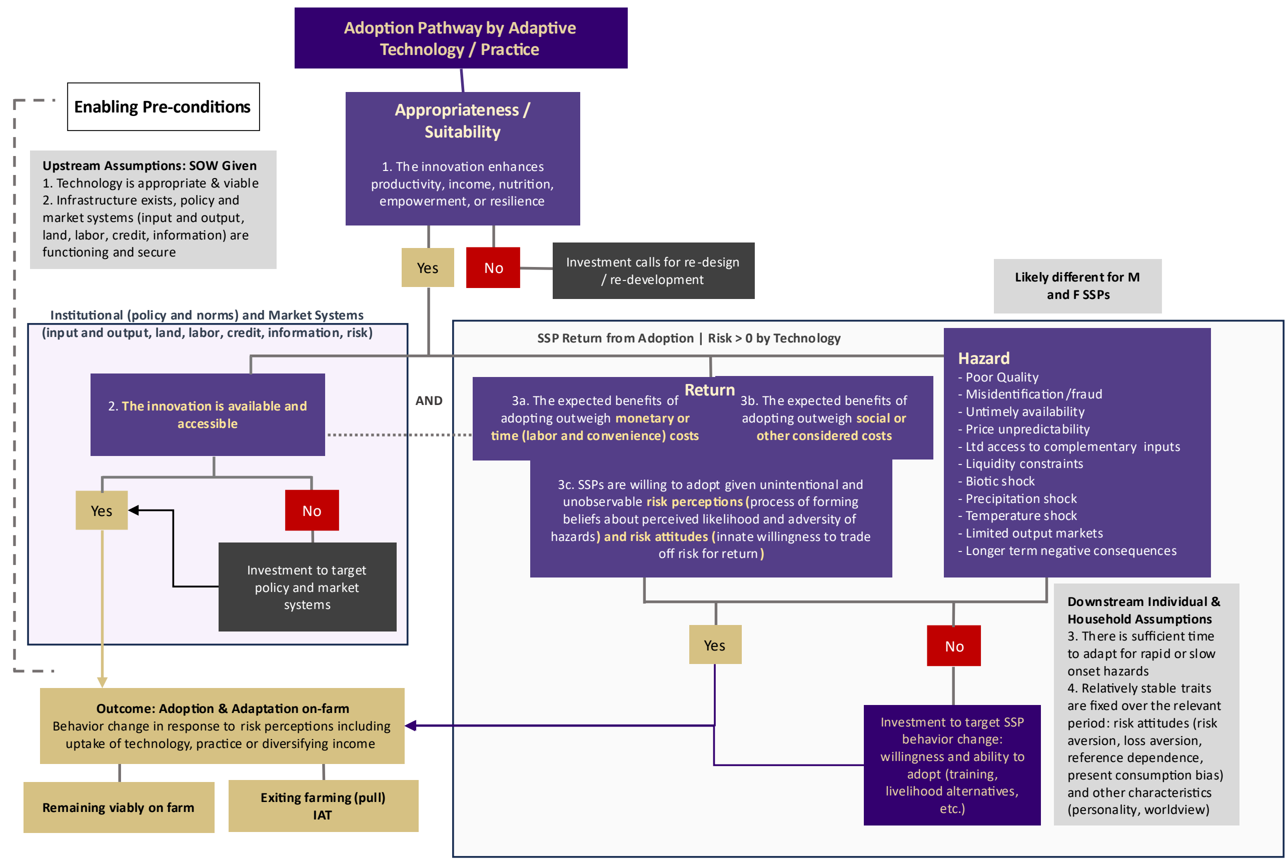
[2] Siegrist and Arvai (2020) argue that risk perceptions research can be grouped in three dominant perspectives: application of heuristics, characteristics of hazards, and characteristics of risk perceivers, including demographic characteristics, knowledge and reasoning, worldviews and value orientations, psychological traits, optimism bias, and cross-cultural differences. In our framework, we assign the application of heuristics and the characteristics of hazards into risk perceptions, and associate innate attitudes towards risk-taking with risk attitudes. The remaining perceiver characteristics, such as demographics or worldview, are better treated as controls in empirical implementations of our conceptual framework as shown in the Appendix.

[3] Tversky and Kahneman (1974) define the representativeness, availability, and anchoring heuristics, respectively, as the tendencies to: judge the probability of an event by how closely it resembles a typical case; judge probability by how easily examples come to mind, which means vivid or recent events are perceived as more likely than they are according to actuarial calculations; and start from an initial estimate and adjust insufficiently, so final judgments stay too close to the anchor. Slovic et. al. (2007) add the affect heuristic, where probability of occurring is affected by the elicited emotions (positive or negative) of the event.

[4] Slovic (1987) presents evidence that dread affects the perceived probability of an event, with perceived probabilities exceeding actuarial probabilities for more dreaded events. We assume that the availability heuristic provides a mechanism through which this occurs, given the tendency to perceive vivid events as more likely than suggested by actuarial probabilities (Tversky and Kahneman, 1974). Siegrist and Arvai (2020) note, however, that the directionality of the causality from affective association to risk perceptions or vice versa is difficult to establish.

risk with potential loss (Kahneman and Tversky 1979), disregard probabilities in favor of emotional salience (Loewenstein et al. 2001), or avoid ambiguity altogether (Ellsberg, 1961).” Kahneman and Tversky’s seminal work on prospect theory relaxes the axioms of expected utility theory and captures loss aversion, reference dependence and probability weighting through additional behavioral parameters in the value function (Kahneman and Tversky, 1979). Later refinements incorporating nonlinear probability weighting led to cumulative prospect theory (Tversky and Kahneman 1992). Our risk attitudes category encompasses not only expected utility theory risk aversion but also loss aversion, reference dependence, and probability weighting from more recent theories of choice under uncertainty.[5]

Figure 1: Technology adoption pathway



Notes: Own elaboration.

To illustrate how risk perceptions and attitudes may lead SSPs to forego a new technology, despite it having a higher expected profitability than a traditional technology, Appendix 1 develops a formal economic model of seed choice under drought risk that is consistent with expected utility theory, prospect theory, and rank-dependent utility. In this model, the SSP chooses between traditional and high-yielding seeds before the season begins, facing a profitability payoff structure for high yielding seeds that depends on assumptions around the probability of drought. Appendix 1 provides numerical examples derived from this setting that build intuition on how perceived probability and adversity of the event (risk perceptions) and risk aversion (risk attitudes) can prevent high-yielding seed adoption despite the higher expected return. From that setting, Appendix 2 derives

[5] Our framework abstracts away from intertemporal decision-making, where preferences consistent with present consumption bias (Thaler and Shefrin, 1981) could lead farmers to under-save harvest income and delay technology adoption in future periods.

three testable predictions and maps these into a regression specification in which perceived likelihood, perceived adversity, and risk aversion enter as regressors with predicted negative coefficients on high-yielding seed adoption. Together, the derived theoretical results and the proposed empirical framework provide guidelines to build the evidence base on the links between risk and technology adoption.

4. Implications for CRIFS research agenda

We demonstrate within a conceptual framework and a plausible formal model (Appendix 1 and 2) how technology adoption can depend not only on expected monetary returns but also on how state-specific returns, event probabilities, risk perceptions, and risk attitudes interact. While the framework presented here does not generate new theoretical insights, it offers a simple utility model that produces results aligned with the risk literature, with the goal of generating testable hypotheses for CRIFS research. This model has direct policy implications. First, climate information systems that provide accurate probability assessments could help align farmer risk perceptions with measured risk, though this may be insufficient on its own. The dread example illustrates how even when perceived probability is identical across farmers, differences in perceived adversity can reverse technology choices. Second, communication that increases the control an SSP may have over the hazard or builds familiarity with the distribution of benefits and costs may mitigate some of the influences of risk perceptions on low technology uptake. Third, economic incentives matter, but supplying technologies with higher expected returns can be insufficient for adoption after accounting for risk aversion. SSP farming and livestock rearing in sub-Saharan Africa and South Asia involves risk, and the CRIFS research agenda is focused on understanding how this affects demand and the likelihood that new technologies will be adopted.

References

Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of development economics*, *96*(2), 159-173.

Ellsberg, D. 1961. Risk, Ambiguity, and the Savage Axioms. *Quarterly Journal of Economics* 75, no. 4: 643–669.

Evans School Policy Analysis and Research Group (EPAR). (2025a). *A food systems framework* (CRIFS Technical Brief No. 396A). University of Washington. https://epar.evans.uw.edu/crifs-technical-brief-a-food-systems-framework/

Evans School Policy Analysis and Research Group (EPAR). (2025b). *Who is a small-scale producer? A proposed operational definition* (CRIFS Technical Brief No. 396B). University of Washington. https://epar.evans.uw.edu/crifs-technical-brief-who-is-a-small-scale-producer-a-proposed-operational-definition/

Elrick-Barr, C. E., Smith, T. F., Thomsen, D. C., & Preston, B. L. (2015). Perceptions of Risk among Households in Two Australian Coastal Communities. *Geographical Research*, *53*(2), 145-159.

Figner, B., & Weber, E. U. (2015). Personality and Risk-Taking. In J. D. Wright (Ed.), *International encyclopedia of the social & behavioral sciences* (2nd ed., pp. 809–813). Elsevier.

Harou, A. P., Madajewicz, M., Michelson, H., Palm, C. A., Amuri, N., Magomba, C., ... & Weil, R. (2022). The joint effects of information and financing constraints on technology adoption: Evidence from a field experiment in rural Tanzania. *Journal of Development Economics*, *155*, 102707.

Höppner, Martin. (2026) Models in Decision-Making Under Risk and Uncertainty. *Journal of Economic Surveys*, 40:304–320. https://doi.org/10.1111/joes.70008

Hsee, C. K., & Weber, E. U. (1998). *Researching risk preference*. Chicago Booth Review. https://www.chicagobooth.edu/review/researching-risk-preference

Kahneman, D., and A. Tversky. 1979. "Prospect Theory: An Analysis of Decisions Under Risk." *Econometrica* 47: 278.

Komarek, A. M., De Pinto, A., & Smith, V. H. (2020). A review of types of risks in agriculture: What we know and what we need to know. *Agricultural Systems*, *178*, 102738.

Liu, E. M. (2013). Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in China. *Review of Economics and Statistics*, *95*(4), 1386-1403.

Loewenstein, G. F., E. U.Weber, C. K. Hsee, and N.Welch (2001). Risk as Feelings. *Psychological Bulletin* 127, no. 2: 267–286.

Reisinger, Andy, Mark Howden, Carolina Vera, et al. (2020). *The Concept of Risk in the IPCC Sixth Assessment Report: A Summary of Cross-Working Group Discussions: Guidance for IPCC Authors.* Intergovernmental Panel on Climate Change.

Siegrist, M. and Árvai, J. (2020), Risk Perception: Reflections on 40 Years of Research. Risk Analysis, 40: 2191-2206. https://doi.org/10.1111/risa.13599.

Slovic, P. (1987). Perception of risk. *Science*, *236*(4799), 280-285.

Slovic, P. Finucane, M.L., Peters E. MacGregor, D.G.. (2007) The affect heuristic, *European Journal of Operational Research*, Volume 177, Issue 3,pp. 1333-1352, ISSN 0377-2217, https://doi.org/10.1016/j.ejor.2005.04.006

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157), 1124–1131.

Tversky, A. (1975). A Critique of Expected Utility Theory: Descriptive and Normative Considerations, *Erkenntnis*, Vol. 9, No. 2. 163-173.

Tversky, A., and D. Kahneman. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty* 5, no. 4: 297–323.

Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The risk perception paradox— 159 implications for governance and communication of natural hazards. *Risk analysis, 33(6), 1049- 160 1065.*Weber, E.U. (2001) Personality and Risk Taking, in International Encyclopedia of the Social & Behavioral Sciences, Editor(s): Neil J. Smelser, Paul B. Baltes, Pergamon, 11274-11276, https://doi.org/10.1016/B0-08-043076-7/01782.

Zappala, G. (2024). Adapting to climate change accounting for individual beliefs. *Journal of Development Economics*, *169*(C).

Appendix 1: Building out a formal model

Our goal with the simple formal model below is to demonstrate how risk perceptions and risk attitudes (condition 3c in Figure 1) can affect technology adoption even when expected benefits of adopting outweigh monetary costs (i.e. expected returns are positive, condition 3a in Figure 1). For that, we present a simple example of technology adoption under uncertainty in a generalized setting that is consistent with theories of decision-making under uncertainty, including expected utility theory and prospect theory. For simplicity, we focus on two features of individual decision-making: i) risk perceptions, distinguishing between the perceived probability and perceived adversity dimensions, and ii) innate risk attitude towards the (perceived) risk.

Consider an SSP who must choose between traditional (T) and improved high-yielding (H) seeds at the beginning of the agricultural season. The farmer faces two states of the world: no drought (ND), with probability $1-p$, and drought (D), with probability p. Seeds cost c_i, with $c_T < c_H$. The uncertain ex-post outcome is crop yield in monetary units x_{ij}, where $j \in \{ND, D\}$, resulting in net return $y_{ij} = x_{ij} - c_i$. We assume yield in the no-drought state is higher than yield in the drought state for both types of seeds ($x_{i,ND} > x_{i,D}$ for $i \in \{T, H\}$), such that drought constitutes the risk to which the farmer is exposed. Let b denote a pay-off baseline or reference point and define $z_{ij} = y_{ij} - b$ as the payoff.

The farmers perceived expected utility of seed i is:

$$V_i = [1 - f(p)]u(z_{i,ND}) + f(p)\,u(z_{i,D})$$

where $f: [0,1] \rightarrow [0,1]$ is a probability weighting function that is strictly increasing with $f(0) = 0$ and $f(1) = 1$. $u: \mathbb{R} \rightarrow \mathbb{R}$ is an instantaneous utility function that is strictly increasing on z. The farmer chooses H if $V_H > V_T$. Risk perceptions determine the perceived probabilities and payoffs to the perceived utility function, and risk attitudes determine how those inputs are evaluated. This framework is sufficiently general to be consistent with multiple theories of decision-making under uncertainty, including expected utility theory, prospect theory, and rank-dependent utility.[6]

We focus our analysis on a return structure where high-yielding seeds offer SSPs three advantages over traditional seeds:

i. Yield and return premium under regular rainfall: $z_{H,ND} > z_{T,ND}$ (A1)
ii. No yield penalty under drought: $x_{H,D} = x_{T,D}$ but $y_{H,D} < y_{T,D}$ due to $c_H > c_T$ (A2)
iii. Higher expected return: $E[y_H] > E[y_T]$ (A3)

This setup characterizes scenarios where farmers may choose traditional over new technologies even when the latter have a higher expected return (Harou et al., 2022). The Appendix proves three results under this decision-making framework and return structure: the relative attractiveness of H over T is reduced by *i)* higher perceived probability of drought, *ii)* higher perceived adversity of the hazard, and *iii)* greater risk aversion as represented by the degree of concavity of the instantaneous utility function u. The Appendix also proposes an empirical framework to test these theoretical results against the data. To build intuition, we provide numerical examples to illustrate each of the three results in the EUT special case, setting $f(p) = p$ and $b = 0$.

We consider the following actuarial drought probability, payoff baseline, and net return parameters: $p = 0.5$, $b = 0$, and $y_{H,D} = 1$, $y_{T,D} = 2$, $y_{T,ND} = 5$, and $y_{H,ND} = 8$. In this scenario, the expected return from high-yielding seeds ($E[y_H] = 4.5$) exceeds that from traditional seeds ($E[y_T] = 3.5$), satisfying A3. Below we present cases where variations in risk perceptions and risk attitudes can reverse this expected return advantage such that farmers choose T over H.

- **Risk perceptions:** As argued, risk perceptions have two dimensions: perceived likelihood, shaped by heuristics, and perceived adversity, shaped by qualitative characteristics of the hazard. Both dimensions may vary systematically across farmers and lead to different input use choices even when

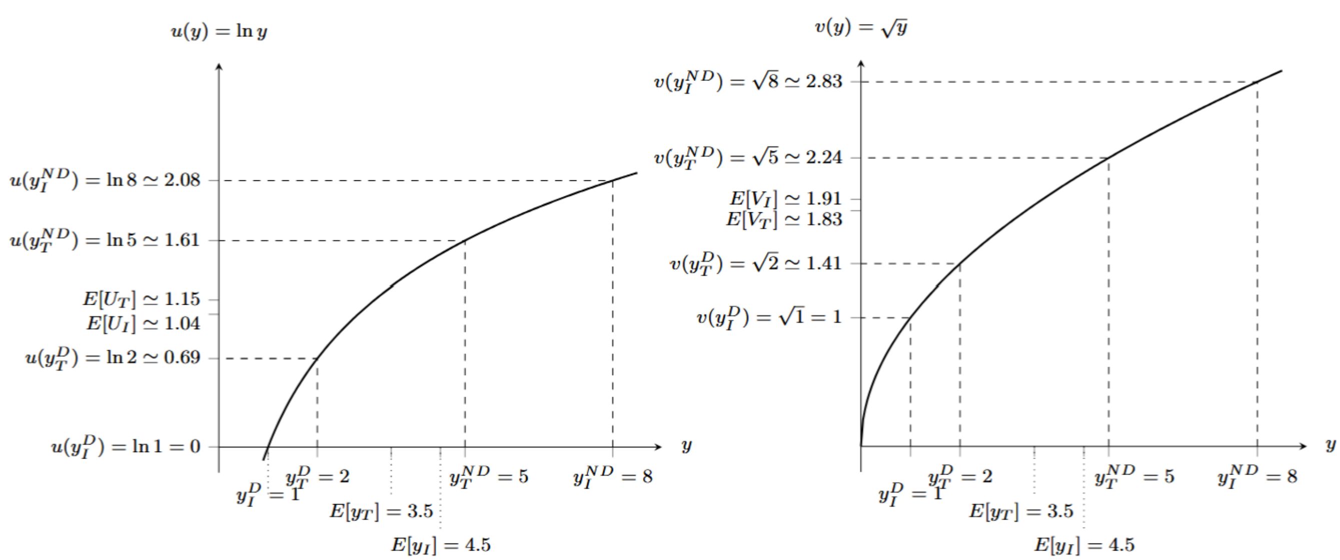
[6] The framework reduces to an expected utility theory setting if $f(p) = p$ and $b = 0$. The model is consistent with the prospect theory setting in Liu (2013) and Liu and Huang (2013) if $f(p) = exp[-(-ln(p)^{\alpha})]$, b_i set to a reference point such as $z_{T,ND}$, and u takes the piece-wise form $u(z) = z^{\alpha}$ for $z \geq 0$ and $u(z_{ij}) = -\lambda(-z_{ij})^{\beta}$ for $z_{ij} < 0$, where $\lambda > 1$ captures loss aversion. The framework also fits rank-dependent utility when $b = 0$ and f matches the decision weights in Diecidue and Wakker (2001), which are increasing in p.

actuarial probabilities and perceived hazard consequences are identical. First, we focus on perceived likelihood and assume that farmers have instantaneous utility $u(y) = ln(y)$. In this setting, farmers choose high-yielding seeds if they perceive that $f(p) < [ln(5) - ln(8)]/[ln(5) - ln(8) - ln(2)] \approx 0.4$, which is less than the actuarial probability of 0.5. This example illustrates that risk attitude equivalent farmers facing identical actuarial probabilities of climate risk may make different choices if their perceived probabilities of the adverse event differ. Empirically, farmers who underestimate drought probabilities irrigate less than farmers with accurate drought probability perceptions (Zappala, 2024).

Second, we illustrate the perceived adversity dimension through an ad hoc modification of our expected utility setting under the assumption that $f(p) = p$ and $u(y) = sqrt(y)$. Let the hazard's qualitative characteristic of dread be represented by a penalty parameter $0 \leq \kappa < y_{H,D} = 1$ that penalizes payoffs in the drought state. Perceived expected utility becomes $V_i = (1-p)u(y_{i,ND}) + pu(y_{i,D} - \kappa)$. With the probability and payoff parameters above, a farmer chooses high-yielding seeds if $\kappa < 1 - \left[\frac{(2-1)-(\sqrt{8}-\sqrt{5})^2}{2(\sqrt{8}-\sqrt{5})}\right]^2 \approx 0.7$ and chooses traditional seeds otherwise. This example, which can also describe unobserved costs of moving from the status quo, shows that even when perceived probability is identical across farmers, differences in perceived adversity can flip technology choices.

- **Risk attitudes:** A decision-maker is said to be risk averse if they prefer a guaranteed payment over a lottery of the same expected value. In the expected utility framework, risk aversion corresponds to Bernoulli utility, a function that links payoffs such as monetary outcomes with subjective personal value, with decreasing slope. As measured by absolute and relative coefficients of risk aversion, a farmer with Bernoulli utility $u(y) = ln(y)$ is more risk averse than one with Bernoulli utility $v(y) = sqrt(y)$, as $ln(y)$ exhibits both higher absolute and relative risk aversion coefficients than $sqrt(y)$. The farmer with $u(y) = ln(y)$ picks traditional seeds while the farmer with $v(y) = sqrt(y)$ chooses high-yielding seeds (see figure 2). This simple example shows how risk aversion can determine which technology is adopted, consistent with empirical findings that increased risk aversion is associated with lower inorganic fertilizer uptake in Ethiopia (Dercon and Christiaensen, 2011).

Figure 2: Risk aversion and seed type choice



Panel A: Log Bernoulli utility *Panel B: Squared root Bernoulli utility*

These simple examples show that two farmers who face identical actuarial climate hazard probabilities and technology options may choose different technologies depending on their risk perceptions and risk attitudes.

Appendix 2: Testable hypotheses

This appendix uses the seed choice model to derive three testable hypotheses and map them into a regression framework. Recall that in the setup, the farmer has strictly increasing instantaneous utility u and chooses high-yielding H seeds over traditional seeds T if $V_H > V_T$, which after rearranging terms is equal to:

$$[1 - f(p)]\,[u(z_{H,ND}) - u(z_{T,ND})] - f(p)\,[u(z_{T,D}) - u(z_{H,D})] > 0 \quad (1)$$

The proofs below maintain the section 3 assumptions that:

i) $f: [0,1] \to [0,1]$ is strictly increasing, with $f(0) = 0$ and $f(1) = 1$,
ii) ii) $u: \mathbb{R} \to \mathbb{R}$ is strictly increasing, and

In addition, we assume the following payoff ordering: $z_{H,ND} > z_{T,ND} > z_{T,D} > z_{H,D}$, which follows from the section three advantages A1–A2 with a common payoff baseline b. Additional assumptions by proposition are listed as required.

Proposition 1: Higher perceived climate hazard probability reduces the relative attractiveness of high-yielding seeds.

Additional assumption: f is differentiable on $(0,1)$, so $f'(p) > 0$ for all $p \in (0,1)$.

Proof: Differentiating $V_H - V_T$. with respect to p:

$$\frac{\partial[V_H - V_T]}{\partial p} = -f'(p)\{[u(z_{H,ND}) - u(z_{T,ND})] + [u(z_{T,D}) - u(z_{H,D})]\} \quad (2)$$

Since u is strictly increasing, $z_{H,ND} > z_{T,ND}$ implies $u(y_{H,ND}) - u(y_{T,ND}) > 0$, and $z_{T,D} > z_{H,D}$ implies $u(z_{T,D}) - u(z_{H,D}) > 0$. Therefore, since $f'(p) > 0$ the derivative in equation 2 is strictly negative. ■

Proposition 2: Higher perceived adversity of the climate hazard reduces the relative attractiveness of high-yielding seeds.

To model perceived adversity, we introduce a dread penalty $\kappa \geq 0$ that reduces the payoff in the drought state, replacing $z_{i,D}$ with $z_{i,D} - \kappa$:

$$V_i^\kappa = [1 - f(p)]\,u(z_{i,ND}) + f(p)\,u(z_{i,D} - \kappa) \quad (3)$$

Additional assumptions: (a) u is strictly concave, and (b) u is differentiable at $z_{i,D} - \kappa$ for $i \in \{T, H\}$ — that is, $\kappa \neq z_{HD}$ and $\kappa \neq z_{TD}$. The Prospect Theory instantaneous utility function u has a kink at $z = 0$, so assumption (b) excludes the two boundary point $\kappa = z_{H,D}$s and $\kappa = z_{T,D}$. This non-differentiable case is handled by the remark below.

Proof. Differentiating the adoption gap with respect to κ:

$$\frac{\partial[V_H^\kappa - V_T^\kappa]}{\partial \kappa} = f(p)\,[u'(z_{T,D} - \kappa) - u'(z_{H,D} - \kappa)] \quad (4)$$

Since $z_{HD} - \kappa < z_{TD} - \kappa$ and u is strictly concave, u' is strictly decreasing, so $u'(z_{TD} - \kappa) < u'(z_{HD} - \kappa)$. The bracketed term is therefore strictly negative. Since $f(p) > 0$, equation (3) is strictly negative. ■

Remark on non-differentiable u. The result extends to $\kappa = z_{H,D}$ or $\kappa = z_{T,D}$ without requiring differentiability. For any $\kappa_2 > \kappa_1 \geq 0$, let $\varepsilon = \kappa_2 - \kappa_1 > 0$. Strict concavity of u implies that $u(x) - u(x - \varepsilon)$ is strictly decreasing in x. Since $z_{H,D} < z_{T,D}$:

$$u(z_{H,D}) - u(z_{H,D} - \varepsilon) > u(z_{T,D}) - u(z_{T,D} - \varepsilon)$$

Rearranging: $u(z_{H,D} - \varepsilon) - u(z_{T,D} - \varepsilon) < u(z_{H,D}) - u(z_{T,D})$, which implies $V_H^{\kappa_2} - V_T^{\kappa_2} < V_H^{\kappa_1} - V_T^{\kappa_1}$ for all $\kappa_2 > \kappa_1$. This argument uses only strict concavity of u and therefore applies to the prospect theory value function at its kink. ■

Proposition 3: A more risk-averse farmer is less likely to adopt high-yielding seeds than a less risk-averse farmer facing identical payoffs and perceived probabilities.

The adoption condition in inequality 1 can be re-written as:

$$\frac{u(z_{H,ND}) - u(z_{T,ND})}{u(z_{T,D}) - u(z_{H,D})} > \frac{f(p)}{1 - f(p)} \tag{5}$$

To prove proposition 3, it suffices to show that for two farmers with different degrees of risk aversion, the more risk averse farmer has a smaller left-hand side ratio. To see why, note that at a perceived probability ratio for which the more risk averse farmer is indifferent between H and T, the less risk averse farmer will choose H. More generally, whenever the more risk averse farmer chooses T, the less risk averse farmer may choose H.

Let farmer A with instantaneous utility u_A be more risk averse in the Arrow-Pratt sense than farmer B with Bernoulli utility u_B. It follows that $u_A = g(u_B)$ for some strictly increasing and strictly concave function g. Defining $a = u_B(z_{H,ND})$, $b = u_B(z_{T,ND})$, $c = u_B(z_{T,D})$, $d = u_B(z_{H,D})$, where $a > b > c > d$ because $z_{H,ND} > z_{T,ND} > z_{T,D} > z_{H,D}$ and u_B is strictly increasing, the left-hand side of inequality 4 becomes:

$$\frac{u_A(z_{H,ND}) - u_A(z_{T,ND})}{u_A(z_{T,D}) - u_A(z_{H,D})} = \frac{k(a) - k(b)}{k(c) - k(d)} \tag{5}$$

By the concavity of k and since $a > b > c > d$, the average slope of g over $[b, a]$ is strictly less than the average slope over $[d, c]$:

$$\frac{g(a) - g(b)}{a - b} < \frac{g(c) - g(d)}{c - d} \tag{6}$$

Rearranging and terms in inequality 6 in combination with 5, we get that:

$$\frac{u_A(z_{H,ND}) - u_A(z_{T,ND})}{u_A(z_{T,D}) - u_A(z_{H,D})} = \frac{k(a) - k(b)}{k(c) - k(d)} < \frac{a - b}{c - d} = \frac{u_B(z_{H,ND}) - u_B(z_{T,ND})}{u_B(z_{T,D}) - u_B(z_{H,D})} \blacksquare \tag{7}$$

Empirical Framework: To bring the propositions from the theoretical framework to data, we present an econometric approach with cross-section data from a hypothetical area where drought is the primary hazard relevant for technology adoption decisions and the payoffs structure for high-yielding seeds reasonably resembles that from our illustrative setting. We assume that the data includes measures of perceived drought probability, perceived drought adversity, and risk aversion. We propose the following linear probability model:

$$y_i = \beta_0 + \beta_1 x_{1.i} + \beta_2 x_{2.i} + \beta_3 x_{3.i} + \gamma Z_i + \varepsilon_i$$

where y_i is a dummy equal to one if household i adopted the high-yielding seed. $x_{1.i}$measures perceived hazard likelihood, obtained by asking households their subjective probability of a drought in the coming season through survey questions. $x_{2.i}$measures perceived hazard adversity, constructed through dread indicators from psychometric instruments following Slovic (1987). $x_{3.i}$measures risk aversion as estimated from experimental lottery choices as in Liu (2013). Z_i is a vector of controls for household demographics, farm characteristics, and technology accessibility that may confound the relationship between risk perceptions, attitudes, and adoption, and ε_i is an error term. Propositions 1, 2, and 3 imply that $\hat{\beta}_1 < 0$, $\hat{\beta}_2 < 0$, and $\hat{\beta}_3 < 0$.

Our framework is suitable for analyzing the adoption of technologies that enhance yields when the hazard's adverse event is not realized and imposes no yield penalty when it does, such as the high-yielding varieties from our example or potentially broader productivity-enhancing inputs. For simplicity, we focused on drought as the single relevant hazard, though our framework applies directly to any setting where a single hazard dominates and the payoff structure resembles the one from our example setup. Deriving hypotheses for multiple hazard settings may require a different empirical approach that is left for future work. The same applies to studying other types of technologies, such as stress-resistant seeds or defensive investments like herbicide and pesticide, whose payoff structures differ from those assumed in our setup.