Loss Aversion and Agricultural Investment: Experimental Evidence from Smallholder Farmers in Kenya

Madison Levine[1] * Sarah Janzen[1] Berber Kramer[2] Kelvin Shikuku[3]

October 18, 2026

Abstract

Smallholder farmers persistently underinvest in productivity-enhancing agricultural inputs. We study whether loss aversion explains this gap. We combine a dynamic model of fertilizer decisions under Cumulative Prospect Theory with a lab-in-the-field experiment involving 209 maize farmers in Kenya, individually eliciting loss aversion parameters via price list lotteries and maximum likelihood estimation. Loss aversion is associated with 1.4 fewer kilograms of fertilizer per unit, 14 percent of the sample mean. This implies that loss aversion operates as an independent barrier to investment, beyond the risk and liquidity constraints that financial products are designed to address. We introduce four decision-making environments to better understand how loss aversion interacts with fertilizer investment when farmers use local seeds alone or have access to index insurance, emergency credit, or drought-tolerant seed technology. We find that the negative association between loss aversion and investment does not weaken when index insurance or emergency credit is available, and that loss aversion reduces willingness to pay for insurance and emergency credit by similar amounts, pointing to the certain upfront payment structure as the common barrier rather than features specific to either contract.

*Corresponding author, ml124@illinois.edu. [1] Department of Agriculture and Consumer Economics, University of Illinois Urbana-Champaign. [2]International Food Policy Research Institute, Markets, Trade and Institutions Unit, Nairobi, Kenya. [3] International Livestock Research Institute, Livestock, Climate, and Environment Program

1. Introduction

Smallholder farmers in developing countries persistently underinvest in agricultural technologies that promise substantial increases in average yields, contributing to low productivity in regions including sub-Saharan Africa (D'Alessandro et al., 2015; Dercon and Christiaensen, 2011; Duflo et al., 2011; Suri et al., 2024). Across this region, limited adoption of fertilizer and other yield-enhancing inputs remains a barrier to agricultural growth and food security (Barrett et al., 2007; Binswanger-Mkhize, 2012; Karlan et al., 2014). One explanation for low investment is uninsured downside risk in agricultural production. When weather is bad, crops have low yields or fail altogether and any investment in agricultural inputs used in production, including fertilizer, is lost. A farmer who anticipates this outcome may rationally reduce investment even when expected returns are positive (Dercon and Christiaensen, 2011). Field evidence supports this mechanism: technologies that reduce downside exposure increase fertilizer use (Emerick et al., 2016). Risk-management products such as index insurance and credit are designed to address this downside risk, and theory predicts that linking them to input purchases can raise adoption (Carter et al., 2016). Evidence from a range of low-income countries shows that access to insurance and credit can raise agricultural investment among smallholder farmers (Bulte et al., 2020; Fink et al., 2020; Karlan et al., 2014; Lane, 2024). Yet take-up of these products remains persistently low, even when they are subsidized or actively marketed (Casaburi and Willis, 2016; Cole and Xiong, 2017; Mobarak and Rosenzweig, 2013).

Explanations for persistently low fertilizer investment and low product take-up have centered on supply-side barriers, including uninsured risk, credit constraints, and product design. These explanations typically assume that farmers evaluate investments and financial products as standard expected utility maximizers, taking up products when expected returns justify the cost. But farmers may instead behave in ways consistent with Cumulative Prospect Theory (CPT) (Barberis, 2013; Kahneman and Tversky, 1979; Koszegi and Rabin, 2006). Loss-averse agents evaluate outcomes relative to a reference point and weight losses more heavily than equivalent gains. This asymmetry between losses and gains represents the key departure from standard expected utility theory and is captured by the loss aversion parameter, with higher loss aversion indicating a stronger penalty on losses relative to equivalent gains. A possibility that has received less attention is that this same behavioral mechanism may simultaneously limit demand for the products designed to address underinvestment, not only investment itself.

CPT could be particularly relevant for fertilizer investment and insurance products: the upfront fertilizer cost falls in the loss domain relative to the status quo reference point

and is intensified by loss aversion, making the investment look worse at the margin even when its expected value is positive. The same logic applies to the insurance premium, which is also a certain upfront payment, and may apply to the anticipated repayment of emergency credit. If loss aversion reduces willingness to engage with risk-management products alongside investment, then expanding the products may not reach the farmers they are meant to help.

Field evidence suggests that farmers behave in ways consistent with loss aversion, and a growing body of work has measured this parameter directly. A systematic review of 17 CPT studies and over 2,300 farmers across Europe finds that loss aversion is consistently detected across field elicitation with farm populations (Finger et al., 2024). Evidence from developing countries shows that this loss aversion shapes investment and product decisions, though not always in the same direction. Liu (2013) shows that more loss-averse farmers adopt higher-yield crop varieties later in rural China, consistent with the prediction that loss aversion reduces risky investment. For insurance demand, Shin et al. (2022) finds that a one-standard-deviation increase in loss aversion is associated with lower demand for index insurance by 12 to 18 percent among Kenyan smallholder farmers, whereas Visser et al. (2020) finds the opposite in South Africa, where loss-averse farmers are more likely to adopt an insured technology package because insurance eliminates the loss they would otherwise face.

This paper focuses on three related questions. First, does farmer loss aversion reduce fertilizer investment? Second, does the negative association between loss aversion and investment weaken when emergency credit converts the certain upfront repayment into a contingent cost triggered only by bad weather, as our CPT model predicts? Third, does loss aversion reduce willingness to pay for index insurance and emergency credit by similar amounts, or does it respond differently across the two products?

To answer these questions, we develop a dynamic CPT model of fertilizer investment that generates structural predictions about optimal investment (Barberis, 2013; Kahneman and Tversky, 1979). We test these predictions with 209 maize farmers in arid and semi-arid lands in Kenya using a four-season fertilizer investment game. Each farmer plays the game under four environments, each defined by a seed type and available financial product(s). The environments are (1) local seeds only, (2) local seeds paired with index insurance (local + insurance), (3) local seeds paired with emergency credit (local + EC), and (4) drought-tolerant seeds without a financial product (DT seeds). Farmers then complete a multiple price list elicitation from which we recover individual values of loss aversion, risk aversion, and probability weighting. We separately elicit willingness to pay for insurance and emergency credit using a Becker-DeGroot-Marschak mechanism. To ensure decisions are incentive compatible,

real payoffs are determined by one randomly selected season from the game or a randomly selected row from the price list.

We have three main findings. First, we find that loss aversion is negatively associated with fertilizer investment. A one-standard-deviation increase in farmer loss aversion is associated with approximately 1.7 fewer kilograms of fertilizer per season, roughly 17 percent of the sample mean in a game calibrated to a one-acre plot. Our specification separately identifies loss aversion from risk aversion, which allows us to ask whether the investment result reflects loss aversion specifically or a more general aversion to risk. Risk aversion shows no significant relationship with fertilizer investment, isolating the pattern at loss aversion specifically.

Second, the negative association between loss aversion and investment does not weaken when insurance or emergency credit is available. Our theoretical model predicts that emergency credit should weaken the negative association between loss aversion and investment: by converting the certain upfront repayment into a contingent cost triggered only by bad weather, emergency credit moves that cost out of the loss domain, weakening the role of loss aversion. The estimated interaction between loss aversion and the local + EC condition is directionally consistent with this prediction but well below the model-implied magnitude.

Third, loss aversion is associated with lower willingness to pay for both insurance and emergency credit. After placing the two products on a comparable per-period expected cost basis, demand curves for insurance and emergency credit are statistically indistinguishable across the price range and within both high- and low-loss-aversion subgroups. The similarity in demand responses across two structurally different contracts points to the certain upfront payment structure they share as the common mechanism, rather than features specific to either product.

We contribute to three strands of literature. First, we contribute to a large literature documenting the existence and relevance of loss aversion across economic domains (Barberis, 2013; Kahneman and Tversky, 1979; O'Donoghue and Somerville, 2018), and field elicitation with farm populations consistently finds it present (Finger et al., 2024; Liu, 2013; Visser et al., 2020; Zhang et al., 2026). We confirm the negative association between loss aversion and agricultural investment in a new setting and extend it by isolating loss aversion from risk aversion: investment tracks loss aversion but not risk aversion, a distinction prior studies in agricultural settings do not make. This matters because it implies that interventions targeting risk aversion alone, such as improved seed varieties that reduce yield variance, may not relieve the investment constraint for the most loss-averse farmers; the relevant barrier is the asymmetric weighting of losses relative to gains, not diminishing sensitivity to outcomes

per se.

Second, we contribute to a literature on agricultural technology adoption that finds evidence that downside weather risk, liquidity constraints, and behavioral frictions are barriers to fertilizer adoption (Bird et al., 2020; Carter et al., 2016; Deutschmann et al., 2025; Duflo et al., 2011; Emerick et al., 2016; Feder et al., 1985; Karlan et al., 2014; Michler et al., 2019; Suri, 2011). We find loss aversion operates as an independent barrier that persists even when index insurance and emergency credit are available, suggesting that access to these products does not remove the behavioral constraint for the most loss-averse farmers.

Third, prior evidence on loss aversion and risk product demand focuses on insurance (Shin et al., 2022), and a separate literature on credit flexibility finds that flexible repayment terms function as implicit insurance (Battaglia et al., 2024; Farrin and Miranda, 2015; Lane, 2024). We extend the demand evidence to emergency credit and find that loss aversion reduces willingness to pay for both insurance and emergency credit by similar amounts, pointing to the certain upfront payment structure as the common barrier rather than features specific to either contract.

These results suggest that the behavioral barrier loss aversion creates is not specific to any single product. The negative association between loss aversion and investment, and between loss aversion and demand, holds across all four experimental environments and across both contract types. Offering both insurance and emergency credit expands the options of risk-management products but does not resolve the behavioral barrier for the most loss-averse farmers. Interventions that directly address how the upfront cost is framed relative to the reference point may be needed to shift investment for this group.

The rest of this paper is as follows. Section 2 develops a dynamic CPT model for optimal agricultural investment under different experimental environments. Section 3 describes the experimental design and CPT parameter elicitation, while Section 4 presents the estimation framework. Section 5 presents our results, and Section 6 concludes.

2. Theoretical Framework

We develop a dynamic model of agricultural investment under CPT to derive testable predictions about how loss aversion shapes fertilizer investment across seed technologies and risk-management products, and demand for insurance and emergency credit (Barberis, 2013; Kahneman and Tversky, 1979). The model takes the four environments as given and asks how a farmer with CPT preferences allocates fertilizer within each. We derive the signs of the predictions analytically from the first-order condition and solve the full dynamic model numerically using backward induction, which confirms the second-order condition and the

signs and provides magnitudes, with parameters calibrated to the local Kenyan context. We present the full derivations, parameterization, and comparative statics in Appendix B.

2.1 Basic Model

A farmer operates over T seasons, choosing fertilizer $Q_{f,t} \geq 0$ at the start of each season before weather $\varepsilon_t \in \{\text{bad, moderate, good}\}$ is realized. Output is produced using fertilizer and a fixed seed quantity under a flexible translog technology $Y(Q_{f,t}, g_t, \varepsilon_t)$, where $g_t \in \{\text{local, DT}\}$ denotes seed technology. Under local seeds, season-t profit is

$$\Pi^{LS}(\varepsilon; Q_{f,t}) = p_Y\, Y(Q_{f,t}, \text{local}, \varepsilon) - p_f Q_{f,t}, \tag{1}$$

where p_Y is the output price and p_f is the fertilizer input price. The fertilizer cost $p_f Q_{f,t}$ is paid at the start of each season before weather realizes.

The farmer evaluates season-t outcomes relative to a reference point R_t. Letting $x_t = \Pi_t(\varepsilon_t; Q_{f,t} \mid g_t, z_t) - R_t$ denote the gain or loss in season t, the farmer maximizes the discounted sum of CPT-weighted values:

$$V_t(s_t) = \max_{Q_{f,t}} \left\{ \sum_{\varepsilon \in E} \omega(\varepsilon)\, v\big(\Pi_t(\varepsilon;\, Q_{f,t} \mid g_t, z_t) - R_t\big) \;+\; \beta \sum_{\varepsilon \in E} p_\varepsilon\, V_{t+1}(s_{t+1}) \right\}, \tag{2}$$

with terminal condition $V_{T+1}(\cdot) = 0$. The first sum applies rank-dependent decision weights $\omega(\varepsilon)$ to the CPT value of current-period outcomes. The second sum applies objective probabilities p_ε to the continuation value; objective rather than decision-weighted probabilities enter here so that probability distortion enters the objective exactly once per period. The state s_t collects the farmer's cash-on-hand W_t and reference point R_t. With $R_t = 0$ fixed, the effective state is the scalar W_t. The CPT value function is kinked at the reference point:

$$v(x) = \begin{cases} x^\sigma & x \geq 0, \\ -\lambda(-x)^\sigma & x < 0, \end{cases} \qquad \sigma \in (0, 1], \quad \lambda \geq 1. \tag{3}$$

The curvature parameter σ captures diminishing sensitivity where a marginal gain or loss matters less the further the outcome is from the reference point. The loss aversion parameter λ is the gain-loss asymmetry. Losses weigh λ times more than equivalent gains. The value function uses symmetric curvature, with the same σ governing diminishing sensitivity for both gains and losses, consistent with the elicitation design and the functional form in (Stott, 2006). Objective probabilities enter through the one-parameter Prelec weighting function $w(p; \alpha) = \exp\{-(-\ln p)^\alpha\}$, which maps objective probabilities into rank-dependent decision

weights $\omega(\varepsilon)$ following the standard CPT construction (Kahneman and Tversky, 1979; Prelec, 1998). The full expressions for $\omega(\varepsilon)$ and the budget constraint are in Appendix B.

We fix $R_t = 0$ for the comparative statics and empirical implementation. Endogenous updating of R_t to realized profit creates a perverse dynamic in which higher investment today raises tomorrow's reference point, making all future outcomes appear as losses and driving optimal investment toward zero for any positive λ. We fix $R_t = 0$ to avoid this degenerate outcome. We show in Appendix B that all signed predictions below are robust to this choice. The fertilizer cost $p_f Q_{f,t}$ is a certain outflow paid before weather is realized. With $R_t = 0$, it is lost when the weather is bad, so the bad-weather outcome falls in the loss domain for all $Q_{f,t} \geq 0$. Because local seeds produce nothing in bad weather, each additional kilogram lowers bad-weather profit by exactly p_f. The derivative of the CPT objective with respect to Q in the bad-weather state is

$$\frac{\partial}{\partial Q}\Big[\omega(\text{bad})\, v\big(\Pi^{LS}(\text{bad}; Q)\big)\Big] = \omega(\text{bad}) \cdot \lambda\sigma\big(-\Pi^{LS}(\text{bad})\big)^{\sigma-1} \cdot \underbrace{\Big(p_Y \frac{\partial Y}{\partial Q}\Big|_{\text{bad}} - p_f\Big)}_{=-p_f<0}. \tag{4}$$

This term is negative and scales linearly with λ. Applying the implicit function theorem to the first-order condition,

$$\frac{\partial Q^*}{\partial \lambda} = -\frac{\partial^2 \mathcal{L}/\partial Q\, \partial \lambda}{\partial^2 \mathcal{L}/\partial Q^2}, \tag{5}$$

the cross-partial in the numerator is negative and the denominator is negative by the second-order condition, so $\partial Q^*/\partial \lambda < 0$. The numerical solution confirms this prediction in the full dynamic model across all parameterizations in the calibrated range.

Prediction 1. $\partial Q^*/\partial \lambda < 0$ under local seeds. Higher loss aversion lowers optimal fertilizer investment.

2.2 Insurance

Under local + insurance, the farmer pays a premium $\phi p_f Q_{f,t}$ each season and receives a payout $\delta p_f Q_{f,t}$ in bad weather. Season-t profit becomes

$$\Pi^{Ins}(\varepsilon; Q_{f,t}) = p_Y\, Y(Q_{f,t}, \text{local}, \varepsilon) - (1+\phi)\, p_f Q_{f,t} + \delta\, p_f Q_{f,t} \cdot \mathbf{1}(\varepsilon = \text{bad}). \tag{6}$$

The certain upfront cost is now $(1+\phi)p_f Q_{f,t}$, larger than under local seeds alone. The payout $\delta p_f Q_{f,t}$ shifts the bad-weather outcome upward but is stochastic and enters through the rank-weighted term $\omega(\text{bad})$. The contract is calibrated to be actuarially fair: $\phi = \delta\, p_{\text{bad}}$,

so

$$\mathbb{E}\big[\Pi^{Ins}(\varepsilon; Q_{f,t})\big] = \mathbb{E}\big[\Pi^{LS}(\varepsilon; Q_{f,t})\big]. \tag{7}$$

A risk-neutral farmer therefore faces the same expected profit per season under local + insurance and local seeds, since expected fertilizer costs are identical under both. Any difference in investment between the two environments reflects CPT preferences rather than expected-value differences.

Prediction 2. $\partial Q^*/\partial\lambda < 0$ under local + insurance, with a magnitude smaller to local seeds.

The payout returns δp_f of each kilogram's cost in bad weather while the premium adds ϕp_f, so each additional kilogram lowers bad-weather profit by $(1+\phi-\delta)p_f$, or 0.44 p_f, rather than p_f. The cross-partial is therefore smaller than under local seeds, but the objective is also flatter, so the slope falls only slightly. Insurance reduces the loss-domain problem without resolving it.

2.3 Emergency Credit

Under local + EC, no premium is required. In bad weather a loan $\kappa p_f Q_{f,t}$ is disbursed. The loan is repaid with interest r at the start of the following season, reducing W_{t+1} by $(1+r)\kappa p_f Q_{f,t}$. Emergency credit is single-period: the repayment resolves within the same dynamic sequence, so no separate debt variable enters the state s_t. Season-t profit is

$$\Pi^{EC}(\varepsilon; Q_{f,t}) = p_Y\, Y(Q_{f,t}, \text{local}, \varepsilon) - p_f Q_{f,t} + \kappa\, p_f Q_{f,t} \cdot \mathbf{1}(\varepsilon = \text{bad}). \tag{8}$$

In bad weather the loan offsets the fertilizer cost. Under full coverage ($\kappa = 1$):

$$\Pi^{EC}(\text{bad};\, Q_{f,t}) = p_Y\, Y(Q_{f,t}, \text{local}, \text{bad}). \tag{9}$$

The fertilizer cost no longer appears in the bad-weather outcome. The bad-weather derivative becomes $\partial\Pi^{EC}(\text{bad})/\partial Q = p_Y\, \partial Y/\partial Q|_{\text{bad}} = 0$. Bad weather remains a loss, but additional fertilizer no longer deepens it, and the bad-weather term in the cross-partial is zero. The cross-partial $\partial^2\mathcal{L}/\partial Q\,\partial\lambda$ is therefore smaller in magnitude than under local seeds or local + insurance:

$$\left|\frac{\partial Q^*}{\partial\lambda}\right|_{\text{EC}} < \left|\frac{\partial Q^*}{\partial\lambda}\right|_{\text{LS}}. \tag{10}$$

The loan repayment lowers next-season wealth by $(1+r)\kappa p_f Q_{f,t}$. With the reference point fixed at zero, wealth affects the farmer only through how much fertilizer the farmer can

afford in later seasons. The repayment therefore does not enter the value function as a loss, and loss aversion does not change its weight.

Prediction 3. $\partial Q^*/\partial\lambda < 0$ under local + EC, smaller in magnitude than under local seeds or local + insurance and zero at calibrated values.

2.4 Drought-Tolerant Seeds

DT seeds differ from local seeds in the production technology. Drought tolerance raises the output floor in bad weather:

$$Y(Q_{f,t}, \text{DT}, \text{bad}) > Y(Q_{f,t}, \text{local}, \text{bad}), \tag{11}$$

while in moderate and good weather DT seeds produce more than local seeds at every positive fertilizer level, $Y(Q_{f,t}, \text{DT}, \varepsilon) > Y(Q_{f,t}, \text{local}, \varepsilon)$ for $Q_{f,t} > 0$. Season-t profit under DT seeds is

$$\Pi^{DT}(\varepsilon; Q_{f,t}) = p_Y\, Y(Q_{f,t}, \text{DT}, \varepsilon) - p_{DT}Q_{DT} - p_f Q_{f,t}, \tag{12}$$

where $p_{DT}Q_{DT}$ is the DT seed cost. Because the bad-weather floor $\bar{Y}_{DT}$ does not depend on fertilizer, the bad-weather outcome is

$$\Pi^{DT}(\text{bad};\, Q_{f,t}) = p_Y \bar{Y}_{DT} - p_{DT}Q_{DT} - p_f Q_{f,t}, \qquad \frac{\partial \Pi^{DT}(\text{bad})}{\partial Q_{f,t}} = -p_f. \tag{13}$$

Drought tolerance raises bad-weather output but not the bad-weather marginal product of fertilizer. At calibrated seed costs the bad-weather outcome remains a loss, and each additional kilogram deepens it by p_f, exactly as under local seeds. The implicit function theorem argument of Prediction 1 therefore applies and $\partial Q^*/\partial\lambda < 0$. How large the effect is relative to local seeds depends on how much cash remains after the seed purchase, because the seed cost tightens the budget for fertilizer in later seasons.

Prediction 4. $\partial Q^*/\partial\lambda < 0$ under DT seeds.

Table 1 summarizes the four signed predictions. All environments share the same direction: loss aversion is negatively associated with fertilizer investment. Local + EC and DT seeds produce a smaller $|\partial Q^*/\partial\lambda|$ than local seeds or local + insurance through distinct channels. The numerical solution of the Bellman equation confirms each prediction and provides the magnitudes reported in Appendix B.

Table 1: Model predictions

Environment	$\partial Q^*/\partial\tilde{\lambda}$	Magnitude	Channel
Local seeds	Negative	Baseline	Fertilizer spending is lost when the weather is bad
Local + insurance	Negative	Slightly smaller	Payout returns part of the bad-weather fertilizer cost
Local + EC	Zero	None	Loan covers the bad-weather fertilizer cost
DT seeds	Negative	Smaller	Output floor does not change the bad-weather cost of fertilizer

Notes. $\tilde{\lambda} = \lambda - 1$ is centered loss aversion, equal to zero under loss neutrality. Bad weather is the only loss state in every environment, so the sign of $\partial Q^*/\partial\tilde{\lambda}$ follows from how an additional kilogram of fertilizer changes the bad-weather outcome. Signs are derived analytically from the first-order condition. Magnitudes relative to local seeds come from the numerical solution of the Bellman equation; see Appendix B.

3. Experiment and Data

3.1 Study Sample and Setting

The experiment was conducted in Machakos and Makueni counties in Kenya, regions classified as arid and semi-arid lands where rainfall is highly variable and drought risk is recurrent. Smallholder maize farmers in these areas operate under substantial production uncertainty with limited capacity to cope with weather-related production shocks, making the setting well-suited for studying how behavioral preferences shape agricultural investment and risk management decisions (D'Alessandro et al., 2015). Participants were recruited from 17 villages drawn from a companion survey sampling frame. Within each village, between 12 and 16 farmers who had participated in earlier surveys were invited to experimental sessions. The variation in session size reflects differences in the size of the village-level sampling frame and the availability of invited farmers at the time of sessions, yielding 209 participants.

Table 2 reports summary statistics at the farmer level. The sample includes 209 farmers. Seventy-eight percent of respondents are female, and the average age is 54 years. Around two-thirds are married. Fifty-six percent have some primary education; smaller shares report secondary or higher education. Households have an average of 5.4 members. Farmers cultivate about 1.3 parcels on average, with a total land size of 3 hectares. All farmers grow maize in the short rains of 2023, and almost all do so in the long rains of 2024.

Table 2: Sample Demographics

	Mean	SD	Min	Max
Female	0.779	0.42	0	1
Age of farmer	53.86	13.69	18	88
Married	0.68	0.47	0	1
Some Primary Education	0.56	0.49	0	1
Some Vocational Education	0.07	0.26	0	1
Some Secondary Education	0.22	0.42	0	1
Some College Education	0.07	0.26	0	1
Household size	5.44	2.38	1	13
Number of cultivated parcels (last 4 seasons)	1.30	0.54	1	4
Total parcel size (ha)	3.02	2.44	0.25	18
Grow maize Short Rains 2023	1.00	0.00	1	1
Grow maize Long Rains 2024	1.00	0.07	0	1
Observations	N = 209			

3.2 Risk and Loss Preference Elicitation

Loss aversion, risk aversion and probability weighting are elicited using a multiple price list procedure. We report the series cards used in the Appendix Tables 5 - 7. Each price list presents the participant with a column of binary choices. Each row offers a choice between a safer option (Option A) and a riskier option (Option B), with payoffs changing row by row so that Option A becomes progressively less attractive as the list descends (Andersen et al., 2006; Bocquého et al., 2023; O'Donoghue and Somerville, 2018). A participant who prefers A at the top will switch to B at the row where the riskier option first becomes preferable and continue choosing B for all remaining rows. The switching row identifies a range of parameter values consistent with their preferences, because a rational participant crosses from A to B at most once.

Each participant completes 27 binary choices across three series, with 10 rows in each of Series 1 and 2 and 7 rows in Series 3. A single series of pure-gain lotteries cannot separately identify value function curvature from probability weighting, because both parameters produce risk-averse behavior in the gain domain. Series 1 and 2 present pure-gain lotteries that vary across rows in both the probability of the high payoff and the size of the payoff, providing variation that traces the shape of the value function and the probability weighting function separately. Series 3 introduces lotteries where one outcome falls below the participant's starting endowment, creating the possibility of a loss relative to the initial reference level. Loss aversion governs how much steeper the value function is below the reference point than above it, so the pattern of switching in Series 3 identifies λ after σ and α are pinned by the pure-gain series.

Parameters are estimated jointly by maximum likelihood using all binary choices each

farmer makes across the three series, rather than reducing each series to a single switching point. For each observed choice, the model computes the CPT value of each lottery using the power value function and the one-parameter Prelec probability weighting function, then models the probability of choosing the riskier option with a logistic rule, following the functional form recommendations of Stott (2006). The likelihood of each farmer's observed choice sequence is then the product of these logistic probabilities across all 27 choices, given their parameter values. Because the three series present lotteries with different probability structures and payoff ranges, the joint likelihood provides the variation needed to separately identify σ, α, and λ from a single estimation. Individual estimates are obtained using the hierarchical maximum likelihood framework of Murphy and Ten Brincke (2018). This approach places a population distribution over individual parameters and updates it iteratively alongside farmer-level estimates, regularizing each farmer's parameters toward the population center and reducing noise from the limited number of choices per farmer.

Table 3 reports the distribution of estimated CPT parameters. The mean loss aversion parameter is 2.64 (SD 1.25), indicating that the average farmer weights losses roughly 2.6 times more than equivalent gains. Similar studies in comparable agricultural settings report mean loss aversion of 2.63 among Vietnamese farmers (Tanaka et al., 2010), 3.47 among Chinese cotton farmers (Liu, 2013), and 3.72 among Kenyan smallholders (Shin et al., 2022), with variation across studies attributable to differences in elicitation design and sample composition. Our estimate of 2.64 falls within this range, consistent with the elicitation identifying loss aversion of plausible magnitude for smallholder farmers in a low-income agricultural setting. We center λ at the loss-neutral value of 1, defining $\tilde{\lambda}_i = \lambda_i - 1$, so that $\tilde{\lambda} = 0$ corresponds to a loss-neutral farmer and positive values reflect increasing sensitivity to losses relative to gains. Centering at one simplifies regression interpretation where the coefficient on $\tilde{\lambda}$ captures the investment or demand difference per unit of loss aversion above the loss-neutral threshold. Figure 1 shows the distribution of $\tilde{\lambda}$ across farmers, with the dashed vertical line marking the loss-neutral threshold at zero. The distribution spans from below -1 to above 4, with the greatest mass concentrated between one and one-and-a-half. Roughly ten percent of farmers fall to the left of the threshold, indicating these farmers weight losses less than equivalent gains, while a substantial share exceed two, reflecting a right-skewed distribution with a long upper tail.

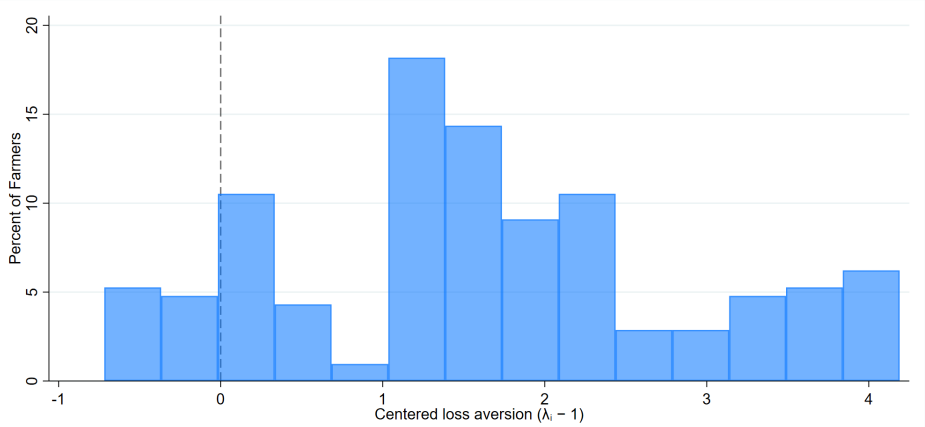


Figure 1: Distribution of estimated loss aversion parameter $\tilde{\lambda}$

The value function curvature parameter averages 0.572 (SD 0.149). Under the power value function, $\sigma < 1$ produces diminishing sensitivity, in which the marginal impact of gains and losses decreases as outcomes move further from the reference point. The sample mean is well below one, indicating that the majority of farmers exhibit diminishing sensitivity on both sides of the reference point. This is consistent with estimates from similar settings: Tanaka et al. (2010) report a mean of 0.59 among Vietnamese rice farmers and Liu (2013) report 0.48 among Chinese cotton farmers. In the investment regressions, σ enters as a control variable alongside $\tilde{\lambda}$ to isolate loss aversion from general value curvature. Figure 2 shows the distribution of σ across farmers, with the majority of estimates falling below one.

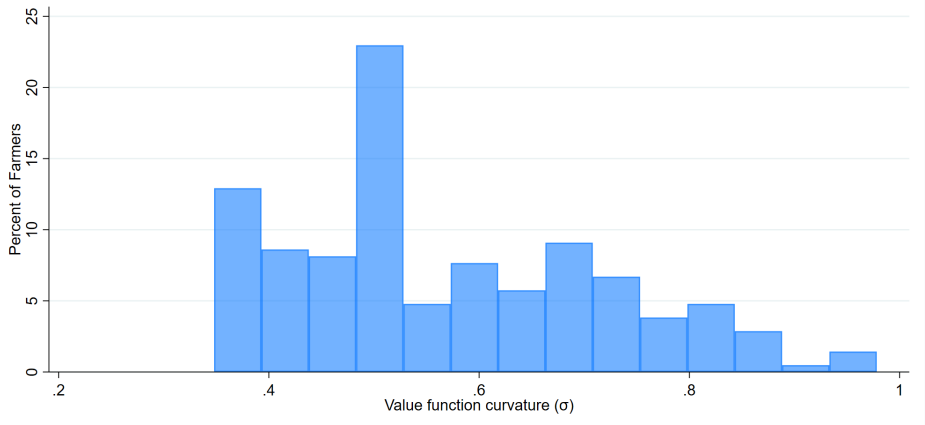


Figure 2: Distribution of estimated value function curvature σ

The probability weighting parameter averages 1.20 (SD 0.08); under the Prelec function, values above one imply S-shaped weighting in which farmers underweight small probabilities and overweight large ones. α is not included in the main investment or demand

regressions. Appendix Figure A1 shows the full distributions of α. Table 3 reports summary statistics for all three estimated parameters.

Table 3: CPT parameter estimates

	Mean	SD	Median
Risk aversion (sigma)	0.572	0.150	0.522
Probability weighting (α)	1.198	0.080	1.187
Loss aversion ($\tilde{\lambda}$)	2.635	1.251	2.465
Observations	N = 209		

Parameters are hierarchical MAP estimates from joint maximum likelihood estimation following Murphy and Ten Brincke (2018). Each farmer completed 27 binary lottery choices across three series (10 + 10 + 7 rows). $\sigma < 1$ indicates diminishing sensitivity; $\alpha > 1$ indicates S-shaped probability weighting; $\tilde{\lambda} > 1$ indicates loss aversion.

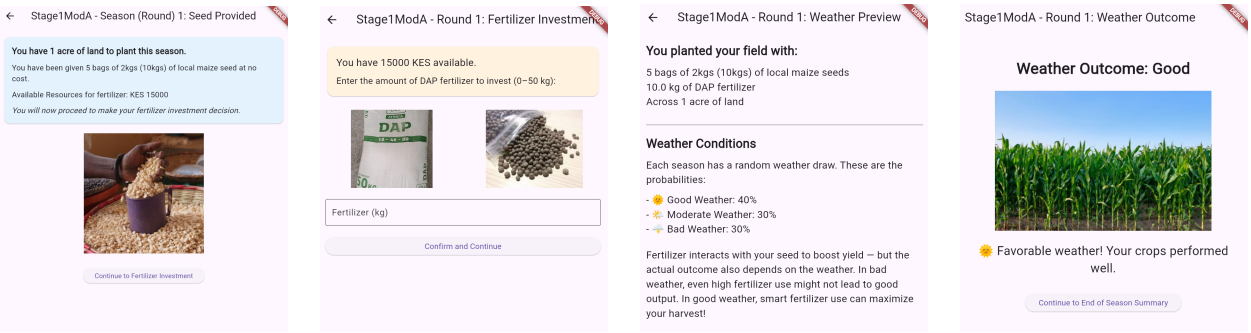
3.3 The "Farming Game"

The farming game places participants in the role of a smallholder maize farmer making fertilizer investment decisions under uncertainty, administered on Android tablets. Farmers aim to maximize earnings across four seasons within each environment, but must decide how much fertilizer to apply before the weather outcome is known. The game is played across four environments. These are local seeds, local + insurance, local + EC, and DT seeds, each described in Section 3.4. The lab-in-the-field approach is appropriate for this purpose. Agricultural outcomes unfold over growing seasons too slow and costly to observe experimentally, and the behavioral mechanisms shaping investment under uncertainty are best identified through a design that compresses this experience into a controlled setting. The game allows us to identify behavioral responses to each product's risk structure in a controlled setting.

Each season proceeds through the same sequence of decisions. At the start of a season, the farmer receives their seed allocation and sees their available endowment. They then decide how much fertilizer to apply, entering an integer quantity in kilograms using a text field; the screen displays the corresponding cost before they confirm. In seasons where the endowment has fallen from earlier losses, the app restricts entry to the quantity the farmer can afford and prompts a revision if they exceed this. Before the weather draw, a recap screen displays the planted inputs and the stated weather probabilities so the farmer can review their choices. The weather outcome is then drawn at random and revealed, along with the season's payoff. Maize output for the realized weather state is calculated from the production function and converted to revenue. The fertilizer cost is subtracted from

the endowment regardless of the weather outcome, so under bad weather, when output falls sharply or to zero, the full fertilizer investment is lost with no revenue to offset it. Net earnings, after subtracting fertilizer costs and accounting for any financial product payout or repayment, update the farmer's endowment and carry forward as the starting budget for the next season. Figure 3 illustrates this sequence as it appeared on the tablet. Farmers complete four seasons in each environment before advancing to the next, allowing them to experience the weather distribution and observe how their fertilizer choices interact with different realizations.

Prior to the main seasons, a trained enumerator demonstrates how weather outcomes are determined using a bag of ten colored chips, four representing good weather, three moderate, and three bad. The farmer draws a chip at random, and the enumerator explains that the tablet replicates this process digitally each season, drawing from the same distribution. Farmers then complete three practice rounds, one for each weather outcome, familiarizing themselves with the app interface and with how their fertilizer choices interact with different realizations.



(a) Seed allocation (b) Fertilizer investment (c) Pre-draw recap (d) Weather outcome

Figure 3: Within-season sequence in the farming game.

Payoffs in each season depend on the farmer's fertilizer choice, the realized weather outcome, and the product available in that environment. At the end of the session, one outcome is selected for payment through a two-stage draw. The first draw determines whether the farming game or the multiple price list elicitation is selected. If the farming game is selected, a second draw identifies one of the four environments at random, and the farmer receives a cash payment as a proportion of their net earnings in the final season of that environment. If the multiple price lotteries series are selected, a second draw identifies one of the three series, and then a row at random from that series, with the farmer's choice in that row determining their payment. Farmers are told at the outset that any decision could determine their payment, giving them an incentive to treat each choice as consequential.

The game is calibrated to match prevailing market conditions in Machakos and Makueni counties. Each farmer begins each environment with an endowment of 5,000 KES, which resets at the start of every new environment so that outcomes in one environment do not affect starting conditions in the next. Within an environment, net earnings carry forward as the starting budget for the following season. A farmer whose endowment reaches zero cannot invest in subsequent seasons and the environment ends at that point. DAP fertilizer costs 120 KES per kilogram and farmers may invest any quantity from 0 to 50 kilograms per season. Maize output is valued at 75 KES per kilogram. Weather is drawn each season according to fixed probabilities. Good weather occurs with probability 0.40, moderate weather with probability 0.30, and bad weather with probability 0.30. In the model of Section 2, the farmer's endowment at the start of each season serves as the reference point, so a season that ends below it, as when the weather is bad and the fertilizer expenditure is lost, falls in the loss domain. Full parameter values are reported in Appendix Table 8.

3.4 Decision Environments

The four environments share the game mechanics and calibration parameters described above. They differ in the financial product available and, in the case of DT seeds, the seed technology used. Local + insurance and local + EC each add a single financial product to the local seed baseline, keeping the seed type fixed, so that any change in investment or demand reflects the product's risk structure. DT seeds replaces the seed technology with drought-tolerant seed, providing downside protection through a different channel.

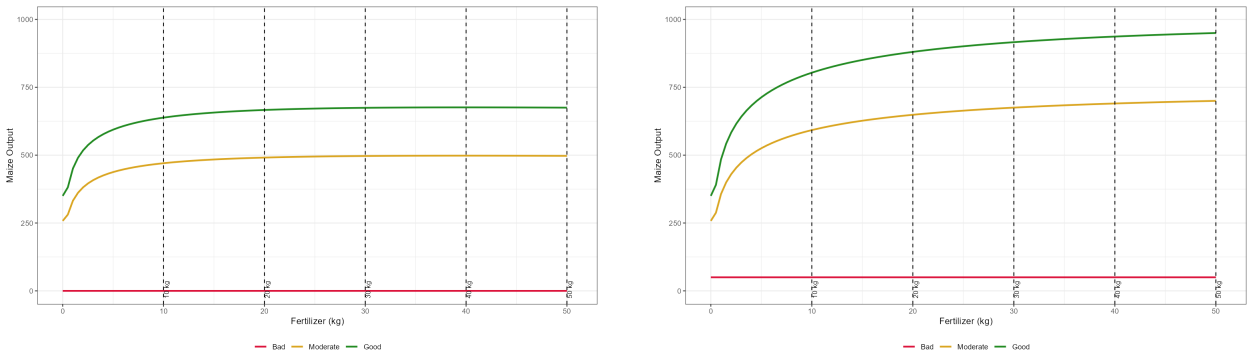
In the *local seeds* environment, farmers receive 10 kilograms of local maize seed per season at no cost. No financial product is available. Output follows a translog production function that scales with fertilizer quantity and the realized weather state. Under bad weather, output falls to zero regardless of fertilizer applied, consistent with complete crop failure under drought. Under moderate and good weather, output increases concavely with fertilizer. Farmers viewed the local seeds production function, shown in the left panel of Figure 4 below, once before beginning the local seeds, local + insurance, and local + EC environments; the figure was not available for reference during play.

In the *local + insurance* environment, an index insurance product covers the farmer against bad-weather fertilizer losses. If bad weather is realized, the farmer receives a payout equal to 80 percent of their fertilizer expenditure. No payout is made in good or moderate weather. The insurance premium equals 24 percent of fertilizer expenditure, set actuarially fair at $p_{\text{bad}} \times \delta = 0.30 \times 0.80 = 0.24$ of fertilizer expenditure. This premium is not charged during the four game seasons; the product is provided at no cost so that investment choices

reflect behavioral responses to the product's risk structure rather than price selection. Formally, the bad-weather payout equals $\delta p_f Q_f$, where $\delta = 0.80$, p_f is the fertilizer price per kilogram, and Q_f is the quantity applied.

In the *local + EC* environment, the financial product is emergency credit rather than insurance. If bad weather is realized, the farmer receives a loan covering the full cost of fertilizer applied at a 20 percent interest rate; no credit is extended in good or moderate weather. The loan is repaid with interest at the end of the following season, after that season's harvest is realized. As with insurance, the product is provided at no cost during the game seasons. Formally, the bad-weather loan amount equals $\kappa p_f Q_f$, where $\kappa = 1$, covering the full cost of fertilizer applied.

In the *DT seeds* environment, drought-tolerant maize seed replaces local seed, providing downside protection through the seed technology rather than a financial product. Farmers receive 10 kilograms of drought-tolerant seed per season at no cost. Under bad weather, output does not fall to zero but instead yields a minimum floor of approximately 50 kilograms regardless of fertilizer applied, as shown in the right panel of Figure 4. Under moderate and good weather, DT seeds produce more output than local seeds at every fertilizer level. Farmers viewed the DT seeds production function once before beginning this environment; the figure was not available for reference during play.



(a) Local seeds (b) DT seeds

Figure 4: Production functions displayed to farmers in the game

Notes: Maize output in kilograms as a function of DAP fertilizer applied, by weather outcome and seed type. Each figure illustrates how fertilizer choices interact with weather realizations under the relevant seed technology.

The insurance premium is set at its actuarially fair rate, calculated from the game parameters, and emergency credit carries a 20 percent interest rate, comparable to the local market rate. Farmers are not told these prices and do not pay them during the four game seasons; each product is made available at no cost. Investment decisions therefore reflect

each farmer's behavioral response to the product's risk structure rather than selection based on the product's price.

3.5 Experimental Design

Each farmer participates in four environments in sequence. These are local seeds, local + insurance, local + EC, and DT seeds. The local seeds environment is always played first and DT seeds always last. The order of local + insurance and local + EC is randomized across farmers. Figure 5 illustrates the sequence.

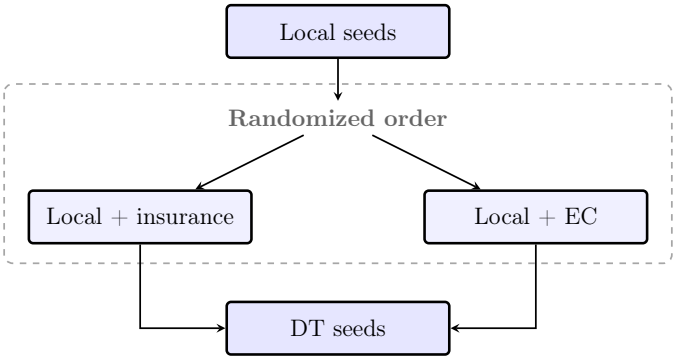


Figure 5: Experimental design

This ordering was chosen to minimize confusion and support learning across environments. Local seeds is always first because it establishes the baseline farming technology before any financial product is introduced. Insurance and emergency credit are played in randomized order because the two environments are the key comparison of interest and both present analogous financial products. Randomizing their sequence ensures that any difference in willingness to pay between the two is not attributable to order effects. DT seeds is always last because it introduces a distinct seed technology that adds complexity to the game. Presenting it earlier would have risked farmers conflating the seed technology with the financial products available in the other environments.

3.6 Willingness-to-Pay Elicitation

After completing seasons 1–4 in each environment, a Becker-DeGroot-Marschak (BDM) elicitation (Becker and DeGroot, 1974) is conducted to elicit demand for access to the available product. The BDM is administered after local + insurance, local + EC, and DT seeds. The local seeds environment has no product and does not conduct a BDM.

Willingness to pay is elicited through a sequence of increasing values. The farmer is shown a series of prices starting low and rising in fixed steps, and asked at each whether they

would be willing to pay that amount for continued access to the product. They respond yes at each price until they are no longer willing, at which point their maximum willingness to pay is recorded as the last price they accepted. For local + insurance, prices are expressed as premium rates per 100 KES of fertilizer investment. For local + EC, they are expressed as interest rates on the same per-expenditure basis. For DT seeds, they are expressed as prices per 2 kilogram bag of maize seed. The farmer's responses are finalized before the strike price is drawn, ensuring that the elicitation reflects genuine willingness to pay rather than strategic adjustment to the drawn price.

The BDM mechanism determines each farmer's outcome as follows. After the farmer states their willingness to pay, a strike price is drawn at random, offering either a 25 percent or 50 percent discount to the prevailing market rate for the product. The prevailing market rate is the actuarially fair premium of 24 KES per 100 KES of fertilizer expenditure for local + insurance, the 20 percent interest rate for local + EC, and 1,100 KES for the 10 kilogram DT seed allocation. If the stated willingness to pay meets or exceeds the strike price, the farmer receives the product and pays the strike price. If it falls below the strike price, the farmer does not receive the product and pays nothing. This mechanism is incentive-compatible.

4. Methods

4.1 Fertilizer Investment

Our primary question is whether loss aversion reduces fertilizer investment and whether this association varies across experimental environments. To answer this question, we measure fertilizer applied per season in kilograms as the primary outcome and proceed in three steps. We first establish baseline differences in mean fertilizer applied between each environment and local seeds (the average kilogram gap attributable to the environment, setting aside behavioral preferences) to characterize investment patterns across the four environments. We then test whether higher loss aversion is associated with lower investment, and finally whether that association is smaller under local + EC as the model predicts.

We begin by pooling observations across all four environments. We then estimate:

$$Q_{is} = \alpha + \beta_C \,\mathrm{Ins}_{is} + \beta_D \,\mathrm{EC}_{is} + \beta_E \,\mathrm{DT}_{is} + X_i'\delta + \phi_s + \varepsilon_{is} \tag{14}$$

where Q_{is} is fertilizer applied by farmer i in season s, Ins_{is}, EC_{is}, and DT_{is} are indicators for the local + insurance, local + EC, and DT seeds environments with local seeds as the

omitted category, X_i is a vector of farmer-level demographic controls, ϕ_s are season fixed effects, and standard errors are clustered at the farmer level throughout. The coefficients β_C, β_D, and β_E capture the average investment gap between each environment and local seeds, abstracting from any role of prospect theory preferences. Because local seeds always occupies the first position and DT seeds the last, position effects prevent separate identification of β_C, β_D, and β_E. Differences relative to local seeds conflate the environment with its place in the sequence. The comparison between local + insurance and local + EC is free of this concern because we randomize their order across farmers, making position orthogonal to environment for those two products.

We next examine whether farmers with higher loss aversion invest less by extending equation (14) with centered loss aversion and risk aversion:

$$Q_{is} = \alpha + \beta_C \,\mathrm{Ins}_{is} + \beta_D \,\mathrm{EC}_{is} + \beta_E \,\mathrm{DT}_{is} + \beta_\lambda \,\tilde{\lambda}_i + \beta_\sigma \,\sigma_i + X_i'\delta + \phi_s + \varepsilon_{is} \tag{15}$$

We include σ_i alongside $\tilde{\lambda}_i$ for a substantive reason. Both parameters are identified from the joint elicitation and both could independently affect investment. Diminishing sensitivity ($\sigma < 1$) compresses perceived payoffs on both sides of the reference point, which could reduce the perceived return to fertilizer independently of how losses are weighted. A specification with only $\tilde{\lambda}_i$ would attribute to loss aversion any investment response that actually reflects value function curvature. Including σ_i lets us ask whether the investment result is specific to the loss aversion channel, which is itself the main empirical question we ask. Because $\tilde{\lambda}_i$ and σ_i do not vary within farmer, we estimate equation (15) by pooled OLS. The coefficient β_λ captures the investment gap between more and less loss-averse farmers, holding environment and season fixed. It does not have a causal interpretation since $\tilde{\lambda}_i$ comes from elicited preferences rather than random assignment. Figure 7 plots the $\tilde{\lambda}$ coefficient estimated separately within each environment as a check that the pooled relationship holds consistently across all four environments.

We then test formally whether this heterogeneity varies across environments by extending equation (15) with interactions between $\tilde{\lambda}_i$ and each environment indicator:

$$\begin{aligned} Q_{is} \;&= \alpha + \beta_C \,\mathrm{Ins}_{is} + \beta_D \,\mathrm{EC}_{is} + \beta_E \,\mathrm{DT}_{is} \\ &\quad + \beta_\lambda \,\tilde{\lambda}_i + \beta_\sigma \,\sigma_i \\ &\quad + \gamma_C\big(\tilde{\lambda}_i \times \mathrm{Ins}_{is}\big) + \gamma_D\big(\tilde{\lambda}_i \times \mathrm{EC}_{is}\big) + \gamma_E\big(\tilde{\lambda}_i \times \mathrm{DT}_{is}\big) + X_i'\delta + \phi_s + \varepsilon_{is} \end{aligned} \tag{16}$$

In this specification, β_λ is the loss aversion coefficient within local seeds, the omitted environment. The interaction terms γ_C, γ_D, and γ_E test whether this differs across the other three environments, and a joint F-test on these terms tests whether it is constant across all four. We also report a farmer fixed effects version, in which the main effects of $\tilde{\lambda}_i$, σ_i, and other time-invariant farmer characteristics are absorbed but the interactions remain identified from within-farmer variation across environments. The position concern from the base specification applies here as well. Because local seeds and DT seeds always occupy fixed positions, the interaction estimates for those environments conflate environment with position. The comparison between γ_C and γ_D is free of this concern because we randomize the order of local + insurance and local + EC across farmers.

5. Results

5.1 Investment by Environment

Average fertilizer investment is similar across all four experimental environments. Figure 6 plots mean use by environment across the four seasons, with 90 percent confidence intervals. In season 1, use ranges from approximately 9.2 kilograms in the local + EC environment to 10.5 kilograms in local seeds. All four environments trend upward over the course of the experiment, and the gaps between environments remain roughly stable across seasons. The confidence intervals overlap substantially at every season, reflecting that average investment is similar across environments at the season level. Table 4 column (1) reports formal regression estimates of these average gaps, pooling across seasons and controlling for farmer demographics and season fixed effects.

5.2 Loss Aversion and Investment

Table 4 presents the regression estimates. Column (1) establishes baseline investment gaps: farmers in local + insurance and local + EC invest approximately 0.93 and 1.13 kilograms less per season than in local seeds, while investment under DT seeds does not differ significantly. These estimates abstract from individual behavioral preferences and characterize how the average investor responds to each environment.

The model predicts that the upfront fertilizer cost is lost when the weather is bad, leaving the farmer below the endowment at the start of the season, and that loss-averse farmers weight this loss more heavily, reducing optimal investment (Prediction 2.1). This prediction holds for local seeds, local + insurance, and DT seeds, where each additional

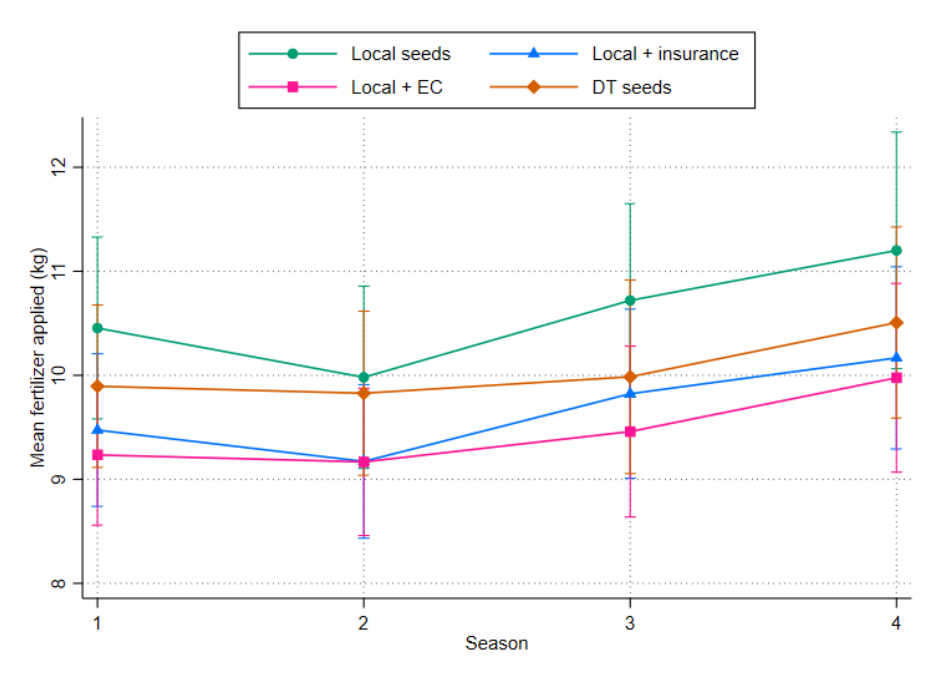


Figure 6: Mean fertilizer applied by environment and season

Note: Mean fertilizer applied (kg) by environment and season, with 90 percent confidence intervals. Sample: all four environments, seasons 1–4.

kilogram of fertilizer still deepens the bad-weather loss, although by less under local + insurance. For local + EC, the emergency credit loan covers bad-weather fertilizer costs, so the model predicts no association between loss aversion and fertilizer investment in that environment (Prediction **??**). We test both the average negative relationship between loss aversion and fertilizer investment and the stronger prediction that this relationship disappears under EC.

Column (2) adds centered loss aversion and risk aversion to the baseline environment indicators. The estimated coefficient on $\tilde{\lambda}$ is -1.373 (SE $= 0.259$, $p < 0.01$), indicating that farmers with higher loss aversion apply significantly less fertilizer. A one-unit increase in $\tilde{\lambda}$ is associated with approximately 1.4 fewer kilograms of fertilizer per season, or roughly 14 percent of the sample mean of 9.9 kilograms. Scaling to the observed dispersion across farmers, a one-standard-deviation increase in $\tilde{\lambda}$ (1.25 units) is associated with approximately 1.7 fewer kilograms, or roughly 17 percent of the mean. This association reflects differences in elicited preferences across farmers rather than a causal effect. Risk aversion shows no significant relationship to investment in any specification, indicating that the investment response reflects loss aversion specifically rather than general diminishing sensitivity. At 1.4 kilograms per unit of $\tilde{\lambda}$, the loss aversion coefficient is larger than either between-environment gap in column (1), indicating that individual variation in loss aversion explains more of the

investment difference than the choice of financial product.

Figure 7 plots the $\tilde{\lambda}$ coefficient from equation (15) estimated separately within each environment. All four point estimates are negative, fall in the range of -1.4 to -1.6 kilograms, and are significant at the 1 percent level. The confidence intervals overlap substantially across environments, indicating that the negative association between loss aversion and investment is consistent across environments and broadly stable in magnitude.

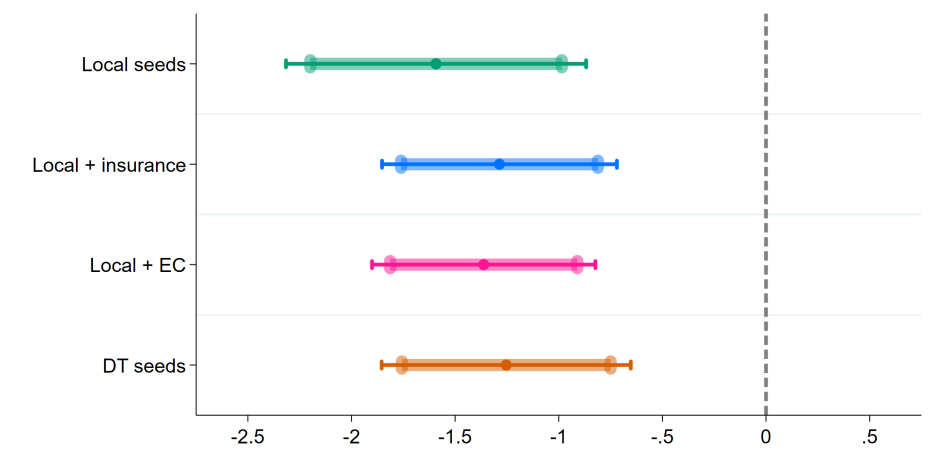


Figure 7: Effect of loss aversion on fertilizer investment by environment

Note: Each point is the OLS estimate of $\tilde{\lambda}$ from equation (15) estimated separately within the indicated environment. This corresponds to the within-environment version of the column (2) specification in Table 4. Controls include farmer demographics and season fixed effects. Thick bars are 90 percent confidence intervals; thin bars are 95 percent confidence intervals. Standard errors clustered at the farmer level.

Column (3) adds interactions between loss aversion and each environment indicator to test Prediction **??**. Figure 8 plots these interaction estimates, each of which measures the difference in the loss aversion coefficient relative to local seeds rather than the total effect in that environment. The cleanest comparison is between the local + insurance and local + EC interactions, since we randomize the order of those two environments across farmers. Both estimates are small and positive, at 0.211 and 0.198 kilograms per unit of $\tilde{\lambda}$ respectively. The direct test that they are equal yields $p = 0.952$, and the joint test that all three interactions are simultaneously zero yields $p = 0.900$. The loss aversion coefficient is therefore similar in magnitude regardless of which financial product is available. The interaction terms for local seeds and DT seeds are not interpretable as pure product effects because those environments always occupy fixed positions in the game sequence, so their estimates conflate environment with position. Column (4) shows that the interaction estimates are nearly unchanged when farmer fixed effects are included, indicating that the null result is not driven by time-invariant farmer characteristics.

The model predicts $dQ^{\star}/d\lambda = 0$ under local + EC. When the bad-weather loan fully covers fertilizer costs, an additional kilogram no longer deepens the bad-weather loss and loss aversion has no effect on the fertilizer margin (Prediction **??**). Relative to the predicted -1.5 kg/unit coefficient under local seeds, this implies an EC interaction of approximately $+1.5$ kg/unit. The estimated interaction is $+0.198$ kg/unit, which is directionally consistent but smaller, indicating the mechanism does not fully operate in practice. One potential explanation, which lies outside the model, is that farmers treat the later EC repayment as a loss, preserving part of the loss aversion effect on fertilizer even when the within-season mechanics eliminate it. In the model the repayment lowers next-season wealth but does not enter the value function as a loss. Either way, the empirical pattern is consistent with the broader result that the loss aversion coefficient is similar in magnitude across environments.

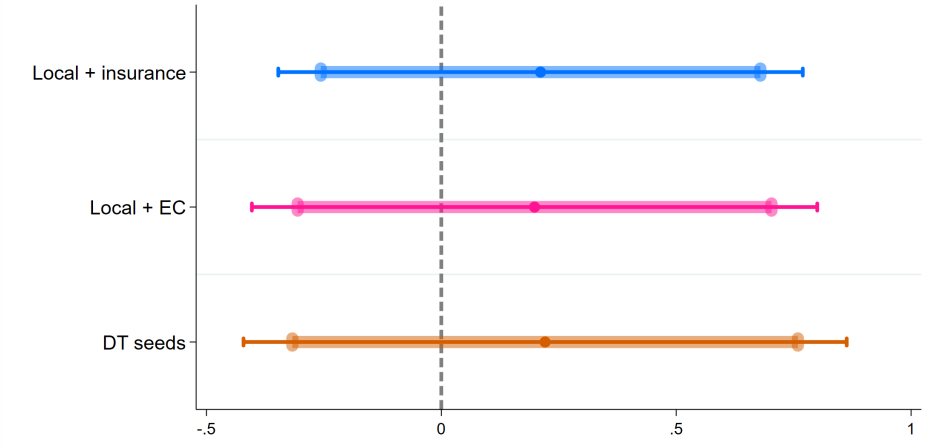


Figure 8: Difference in the loss aversion effect on investment relative to local seeds

Note: Each point is the estimated interaction of centered loss aversion with the indicated environment indicator, from equation (16), column (3) of Table 4. A value of zero indicates the loss aversion coefficient is the same as in local seeds; a positive value indicates it is smaller. Thick bars are 90 percent confidence intervals; thin bars are 95 percent confidence intervals. Standard errors clustered at the farmer level.

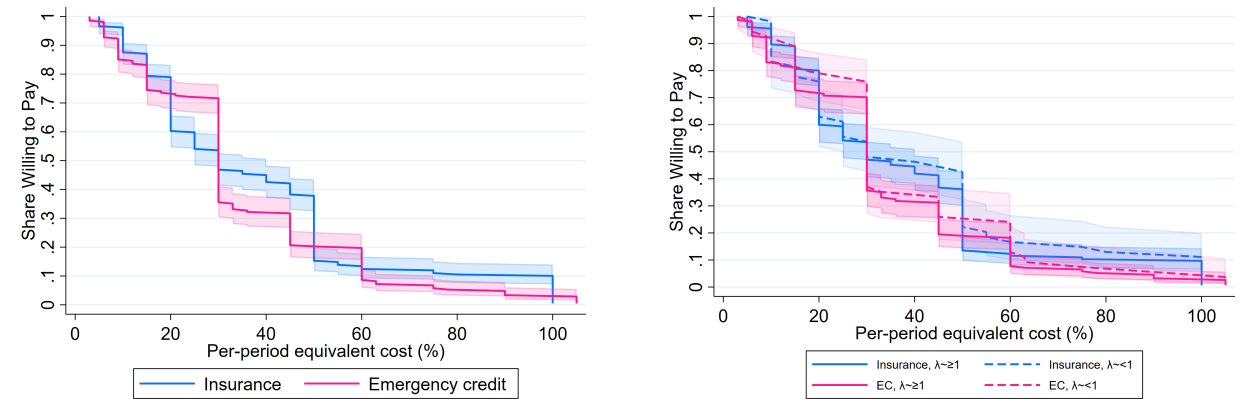
Table 4: Loss aversion and fertilizer investment

	(1) OLS Environments	(2) OLS $+\tilde{\lambda}$, σ	(3) OLS $+\tilde{\lambda} \times$ env.	(4) Farmer FE $+\tilde{\lambda} \times$ env., FE
A. Environment (baseline: local seeds)				
Local + insurance	-0.930***	-0.930**	-1.275*	-1.275*
	(0.358)	(0.358)	(0.684)	(0.682)
Local + EC	-1.130***	-1.130***	-1.454*	-1.454*
	(0.393)	(0.393)	(0.749)	(0.748)
DT seeds	-0.535	-0.535	-0.896	-0.896
	(0.423)	(0.423)	(0.783)	(0.781)
B. Behavioral parameters				
Loss aversion ($\tilde{\lambda}$)		-1.373***	-1.531***	
		(0.259)	(0.345)	
Risk aversion (σ)		2.367	2.367	
		(2.547)	(2.548)	
C. Loss aversion $\times$ environment				
$\tilde{\lambda} \times$ local + insurance			0.211	0.211
			(0.283)	(0.283)
$\tilde{\lambda} \times$ local + EC			0.198	0.198
			(0.305)	(0.305)
$\tilde{\lambda} \times$ DT seeds			0.221	0.221
			(0.326)	(0.325)
Season fixed effects	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	No
Farmer fixed effects	No	No	No	Yes
Observations	3,344	3,344	3,344	3,344
Adj. R^2	0.033	0.080	0.080	0.532
p: interactions jointly zero			0.900	0.899
p: Insurance interaction = EC interaction			0.952	0.952

Standard errors in parentheses. Dependent variable is fertilizer applied (kg). Columns (1)–(3) are OLS. Column (4) has farmer fixed effects. Standard errors clustered at the farmer level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Demand for Insurance and Emergency Credit

The investment results establish that loss aversion is associated with lower fertilizer use regardless of which financial product is available. We next ask whether the same pattern holds at the extensive margin of demand, measured using the BDM willingness-to-pay elicitation described in Section 3.6. The model in Section 2 does not generate predictions for willingness to pay, so we treat demand as an empirical question. Both products require the farmer to agree to a cost before the weather is known, the insurance premium in every season and the emergency credit repayment after a bad season, and loss aversion may raise the weight on each cost relative to the reference point. If loss aversion is associated with lower willingness to engage with products but equally so across insurance and emergency credit, then demand curves for the two products should be statistically indistinguishable once placed on a comparable cost basis.



(a) Pooled demand curves

(b) By loss aversion group

Figure 9: Demand for local + insurance and actuarially adjusted local + EC

Note: EC willingness to pay is multiplied by three to place both contracts on the same per-period expected cost basis; the bad-weather probability is 1/3 in the game, so EC interest is triggered one period in three on average. Panel (b) splits the sample at centered loss aversion $\tilde{\lambda} \geq 1$. Shaded bands are 90 percent Wilson confidence intervals.

Figure 9 presents non-parametric demand curves for local + insurance and actuarially adjusted local + EC. To make the two products comparable, we multiply EC willingness to pay by three. The adjustment converts from a per-incidence interest rate to a per-period expected cost basis by dividing by the bad-weather probability (1/3), placing EC on the same actuarial footing as the insurance premium. Panel (a) shows the pooled demand curves. After this adjustment, the two schedules are nearly identical across the full price range, with 90 percent confidence bands overlapping at every point. Panel (b) splits the sample at $\tilde{\lambda} = 1$. Farmers with higher centered loss aversion ($\tilde{\lambda} \geq 1$) show lower willingness

to pay for both products than less loss-averse farmers ($\tilde{\lambda} < 1$), consistent with the investment results. Within each group, however, insurance and emergency credit demand curves track closely and confidence bands overlap throughout the price range. Loss-averse farmers show lower demand for both products by a similar amount, leaving relative demand between them unchanged.

6. Conclusion

Smallholder farmers in our study apply on average 9.9 kilograms of fertilizer per season, below the risk-neutral optimum of 14 kilograms implied by the calibrated production function at representative wealth levels[1], and take-up of insurance and emergency credit products designed to encourage investment remains persistently low. One explanation is loss aversion. Farmers who weight losses more heavily than equivalent gains face a larger subjective cost of the upfront fertilizer expenditure, which falls in the loss domain before weather realizes. We develop a model of fertilizer investment under CPT that generates three predictions. Loss aversion should reduce investment in environments where fertilizer retains downside weather risk.Emergency credit, which covers bad-weather fertilizer costs through a post-harvest loan, removes this loss-domain exposure, so the model predicts a smaller loss aversion coefficient in that environment than in the others. And loss aversion should reduce demand for both insurance and emergency credit by similar amounts, since the certain premium and the anticipated repayment each appear as losses relative to the reference point.

Each prediction follows from the same mechanism. The fertilizer expenditure is a certain upfront cost while the revenue gain is uncertain and weather-contingent. This places the cost in the loss domain, and loss aversion increases its subjective weight, reducing optimal investment below the risk-neutral benchmark. Emergency credit converts this certain cost into a contingent post-harvest repayment, removing the loss-domain placement and, with it, the predicted loss aversion effect on investment. The insurance premium and the EC repayment are each certain outflows that sit in the loss domain by the same logic, so loss aversion should reduce demand for both products by comparable amounts regardless of their payout structures.

The investment results confirm the first prediction; the second holds in direction but not in magnitude. A one-standard-deviation increase in centered loss aversion is associated with approximately 1.7 fewer kilograms of fertilizer per season, roughly 17 percent of the

[1]In the local seeds environment, the risk-neutral profit-maximizing fertilizer quantity implied by the calibrated production function is 14 kilograms per season; sample mean investment of 9.9 kilograms across all four environments falls well below this benchmark.

sample mean. All four point estimates across environments are negative and significant at the 1 percent level. Our model predicts the loss aversion coefficient to be zero under emergency credit, with a model-implied interaction of approximately +2.0 kg per unit of $\tilde{\lambda}$. The estimated EC interaction is +0.198 kilograms, directionally consistent but smaller, suggesting the mechanism only partially operates in practice.

The demand results reinforce this picture. After adjusting for the actuarial structure of the two products, willingness to pay for insurance and emergency credit is nearly identical at both elicited price points. Splitting the sample by loss aversion, farmers with higher centered loss aversion show lower demand for both products than less loss-averse farmers, and within each group the demand curves for the two products track closely throughout. Loss aversion is associated with lower demand for both products by comparable amounts, leaving relative demand between them unchanged.

These conclusions come with several caveats. First, the investment decisions in this study are made inside a lab-in-the-field setting, and the magnitudes of the loss aversion effects on fertilizer use may not translate directly to field settings where farmers face additional constraints and longer planning horizons. Second, the CPT parameters are elicited at a single point in time per farmer, so we cannot rule out transient factors correlated with loss aversion at elicitation that also affect investment and demand. Third, because the local seeds environment always occupies the first position in the game sequence and DT seeds always the last, environment-specific estimates for those two environments reflect position as well as product and cannot be interpreted as pure product effects.

Loss aversion operates through the loss domain of the fertilizer expenditure itself rather than through features specific to insurance or emergency credit. Offering farmers more products does not resolve this barrier. Interventions that restructure the timing of payments may be more effective at reaching loss-averse farmers. Casaburi and Willis (2016) show that collecting insurance premiums at harvest rather than at planting raises take-up substantially among Kenyan contract farmers. If the channel is loss-domain placement of the upfront premium, then analogous timing adjustments for emergency credit repayment may generate similar effects on demand and on ex-ante investment. Loss-averse farmers invest less and demand less regardless of which product is available, and restructuring when costs fall relative to revenue has a clearer theoretical basis for reaching them than expanding the set of products does.

References

Andersen, S., Harrison, G. W., Lau, M. I., and Rutström, E. E. (2006). Elicitation using multiple price list formats. *Experimental Economics*, 9(4):383–405.

Barberis, N. C. (2013). Thirty Years of Prospect Theory in Economics: A Review and Assessment. *Journal of Economic Perspectives*, 27(1):173–196.

Barrett, C. B., Barnett, B. J., Carter, M. R., Chantarat, S., Hansen, J. W., Mude, A. G., Osgood, D., Skees, J. R., Turvey, C. G., and Ward, M. N. (2007). Poverty Traps and Climate Risk: Limitations and Opportunities of Index-Based Risk Financing. *SSRN Electronic Journal*.

Battaglia, M., Gulesci, S., and Madestam, A. (2024). Repayment Flexibility and Risk Taking: Experimental Evidence from Credit Contracts. *Review of Economic Studies*, page rdad107.

Becker, G. M. and DeGroot, M. H. (1974). Measuring Utility by a Single-Response Sequential Method (1964). In *Economic Information, Decision, and Prediction*, pages 317–328. Springer Netherlands, Dordrecht.

Binswanger-Mkhize, H. P. (2012). Is There Too Much Hype about Index-based Agricultural Insurance? *Journal of Development Studies*, 48(2):187–200.

Bird, S. S., Carter, M. R., Lybbert, T. J., Mathenge, M. W. K., Njeru, T. N., and Tjernström, E. (2020). Filling a niche? The maize productivity impacts of adaptive breeding by a local seed company in Kenya.

Bocquého, G., Jacob, J., and Brunette, M. (2023). Prospect theory in multiple price list experiments: further insights on behaviour in the loss domain. *Theory and Decision*, 94(4):593–636.

Bulte, E., Cecchi, F., Lensink, R., Marr, A., and Van Asseldonk, M. (2020). Does bundling crop insurance with certified seeds crowd-in investments? Experimental evidence from Kenya. *Journal of Economic Behavior & Organization*, 180:744–757.

Carter, M. R., Cheng, L., and Sarris, A. (2016). Where and how index insurance can boost the adoption of improved agricultural technologies. *Journal of Development Economics*, 118:59–71.

Casaburi, L. and Willis, J. (2016). Time vs. State in Insurance: Experimental Evidence from Contract Farming in Kenya. *SSRN Electronic Journal*.

Cole, S. A. and Xiong, W. (2017). Agricultural Insurance and Economic Development. *Annual Review of Economics*, 9(1):235–262.

D'Alessandro, S. P., Caballero, J., Lichte, J., and Simpkin, S. (2015). Kenya agricultural sector risk assessment. Agriculture Global Practice Technical Assistance Paper 97887, World Bank Group.

Dercon, S. and Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, 96(2):159–173.

Deutschmann, J. W., Duru, M., Siegal, K., and Tjernström, E. (2025). Relaxing multiple agricultural productivity constraints at scale. *Journal of Development Economics*, 174:103409.

Duflo, E., Kremer, M., and Robinson, J. (2011). Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya. *American Economic Review*, 101(6):2350–2390.

Emerick, K., De Janvry, A., Sadoulet, E., and Dar, M. H. (2016). Technological Innovations, Downside Risk, and the Modernization of Agriculture. *American Economic Review*, 106(6):1537–1561.

Farrin, K. and Miranda, M. J. (2015). A heterogeneous agent model of credit-linked index insurance and farm technology adoption. *Journal of Development Economics*, 116:199–211.

Feder, G., Just, R. E., and Zilberman, D. (1985). Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change*, 33(2):255–298.

Finger, R., Garcia, V., McCallum, C., and Rommel, J. (2024). A note on European farmers' preferences under cumulative prospect theory. *Journal of Agricultural Economics*, 75(1):465–472.

Fink, G., Jack, B. K., and Masiye, F. (2020). Seasonal Liquidity, Rural Labor Markets, and Agricultural Production. *American Economic Review*, 110(11):3351–3392.

Kahneman, D. and Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47(2):263.

Karlan, D., Osei, R., Osei-Akoto, I., and Udry, C. (2014). Agricultural Decisions after Relaxing Credit and Risk Constraints. *The Quarterly Journal of Economics*, 129(2):597–652.

Koszegi, B. and Rabin, M. (2006). A Model of Reference-Dependent Preferences. *The Quarterly Journal of Economics*, 121(4):1133–1165.

Lane, G. (2024). Adapting to Climate Risk With Guaranteed Credit: Evidence From Bangladesh. *Econometrica*, 92(2):355–386.

Liu, E. M. (2013). 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.

Michler, J. D., Tjernström, E., Verkaart, S., and Mausch, K. (2019). Money Matters: The Role of Yields and Profits in Agricultural Technology Adoption. *American Journal of Agricultural Economics*, 101(3):710–731.

Mobarak, A. M. and Rosenzweig, M. R. (2013). Informal Risk Sharing, Index Insurance,

and Risk Taking in Developing Countries. *American Economic Review*, 103(3):375–380.

Murphy, R. O. and Ten Brincke, R. H. W. (2018). Hierarchical Maximum Likelihood Parameter Estimation for Cumulative Prospect Theory: Improving the Reliability of Individual Risk Parameter Estimates. *Management Science*, 64(1):308–326.

O'Donoghue, T. and Somerville, J. (2018). Modeling Risk Aversion in Economics. *Journal of Economic Perspectives*, 32(2):91–114.

Prelec, D. (1998). The Probability Weighting Function. *Econometrica*, 66(3):497.

Shin, S., Magnan, N., Mullally, C., and Janzen, S. (2022). Demand for Weather Index Insurance among Smallholder Farmers under Prospect Theory. *Journal of Economic Behavior & Organization*, 202:82–104.

Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and Uncertainty*, 32(2):101–130.

Suri, T. (2011). Selection and Comparative Advantage in Technology Adoption. *Econometrica*, 79(1):159–209.

Suri, T., Udry, C., Aker, J. C., Barrett, C. B., Bergquist, L. F., Carter, M., Casaburi, L., Osei, R. D., Gollin, D., Hoffmann, V., Jayne, T., Karachiwalla, N., Kazianga, H., Magruder, J., Michelson, H., Startz, M., and Tjernstrom, E. (2024). Agricultural Technology in Africa. *Journal of Economic Perspectives*, 36(1):33–56.

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

Visser, M., Jumare, H., and Brick, K. (2020). Risk preferences and poverty traps in the uptake of credit and insurance amongst small-scale farmers in South Africa. *Journal of Economic Behavior & Organization*, 180:826–836.

Zhang, W., Jin, Y., and Xu, B. (2026). Farmers' Risk and Ambiguity Preferences and Fertilizer Use Behaviors: Experimental Evidence From Taihu Basin in China. *Agricultural Economics*, 57(1):e70063.

Appendix

A. Figures and Tables

Figure A1 shows the distributions of the probability weighting α across the 209 farmers in the sample. This is estimated jointly with λ and σ from the three-series lottery choice procedure described in the CPT Parameter Elicitation subsection, using the hierarchical maximum likelihood framework of Murphy and Ten Brincke (2018). Under the one-parameter Prelec functional form, $\alpha = 1$ corresponds to linear probability weighting with no distortion, $\alpha < 1$ produces an inverse-S shaped weighting function in which small probabilities are overweighted and large probabilities are underweighted, and $\alpha > 1$ produces the opposite pattern. The sample mean is 1.198 (SD 0.080, median 1.187), indicating that probability weighting is on average S-shaped among these farmers. α is not included in the main investment or demand regressions.

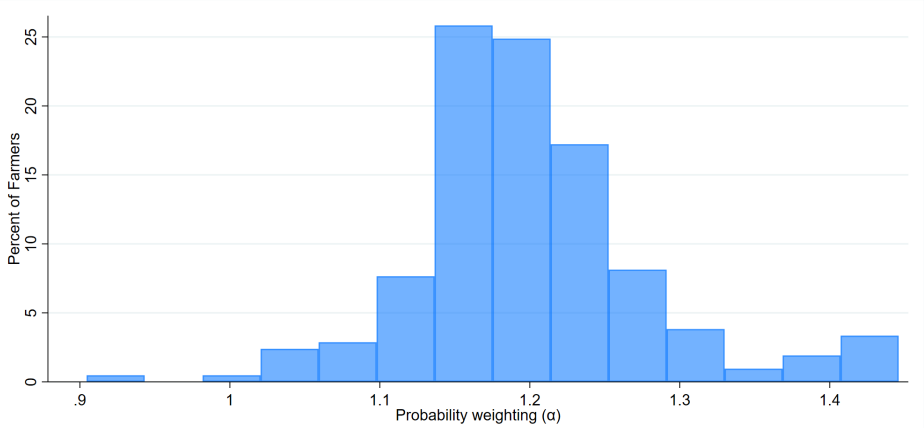


Figure A1: Distribution of probability weighting parameter α

Notes: Distribution of the probability weighting parameter α across the 209 sample farmers. Parameters are hierarchical maximum likelihood estimates from the joint estimation described in Section 3. Under the one-parameter Prelec form, $\alpha = 1$ corresponds to linear probability weighting and $\alpha < 1$ to inverse-S shaped weighting.

Appendix Tables 5–7 report the lottery choice cards used to elicit CPT parameters. Each participant completed all three series. In each row, the participant chose between Option A and Option B, with probabilities shown in parentheses and payoffs denominated in Kenyan Shillings. Series 1 and 2 use pure-gain lotteries to distinguish value curvature from probability weighting. Series 3 introduces losses relative to the experimental endowment and identifies loss aversion. The estimation uses all binary choices from the three series jointly, rather than relying only on switching rows.

Table 5: Lottery cards: Series 1

	Option A		Option B	
Row	(0.30) KES	(0.70) KES	(0.10) KES	(0.90) KES
1	271	253	288	250
2	271	253	301	250
3	271	253	318	250
4	271	253	342	250
5	271	253	374	250
6	271	253	416	250
7	271	253	463	250
8	271	253	566	250
9	271	253	694	250
10	271	253	950	250

Payoffs in Kenyan Shillings (KES). Probabilities in parentheses. Option A is constant across rows; the low-probability prize in Option B increases from row 1 to row 10.

Table 6: Lottery cards: Series 2

	Option A		Option B	
Row	(0.90) KES	(0.10) KES	(0.70) KES	(0.30) KES
1	390	350	430	250
2	390	350	436	250
3	390	350	439	250
4	390	350	448	250
5	390	350	458	250
6	390	350	466	250
7	390	350	486	250
8	390	350	504	250
9	390	350	533	250
10	390	350	560	250

Payoffs in Kenyan Shillings (KES). Probabilities in parentheses. Option A is constant across rows; the high-probability prize in Option B increases from row 1 to row 10.

Table 7: Lottery cards: Series 3

	Option A		Option B	
Row	(0.50) KES	(0.50) KES	(0.50) KES	(0.50) KES
1	700	−100	775	−325
2	660	−100	775	−325
3	640	−100	775	−325
4	640	−150	775	−300
5	640	−200	775	−275
6	640	−225	775	−250
7	640	−250	775	−225

Payoffs in Kenyan Shillings (KES). Probabilities in parentheses. Negative values indicate losses relative to the endowment. Each row offers the same gain from Option B (775 KES) against a larger potential loss; Option B weakly dominates in row 7. Moving across rows changes the gain-loss tradeoff between the two options. These choices provide the main identifying variation for λ in the joint CPT estimation.

Table 8: Game parameters

Parameter	Value
A. Prices and endowments	
Starting endowment	5,000 KES
Fertilizer price (DAP)	120 KES/kg
Maize output price	75 KES/kg
Fertilizer quantity range	0–50 kg
Seed allocation per season: local	10 kg
Seed allocation per season: DT	10 kg
B. Weather	
Good weather probability	0.40
Moderate weather probability	0.30
Bad weather probability	0.30
Bad weather output: local seeds	0 kg (complete crop failure)
Bad weather output: DT seeds	50 kg (minimum yield floor)
C. Financial product terms	
Insurance premium rate (ϕ)	24% of fertilizer expenditure
Insurance payout rate (δ)	80% of fertilizer expenditure
Emergency credit interest rate	20%
D. Production function (translog)	
Seed coefficient: local (β_S)	0.15
Seed coefficient: DT (β_{DT})	0.15
Fertilizer coefficient (β_F)	0.06
Seed quadratic: local (γ_S)	-0.01
Seed quadratic: DT (γ_{DT})	-0.01
Fertilizer quadratic (γ_F)	-0.03
Seed $\times$ fertilizer: local (δ_{SF})	0.07
Seed $\times$ fertilizer: DT (δ_{DTF})	0.10
Weather multiplier: good	0.95
Weather multiplier: moderate	0.70

B. Model Setup

B.1 Timing, Technology, and Profit

Time is discrete and indexed by seasons $t = 1, \ldots, T$. In each season the farmer observes the state $s_t = W_t$, cash-on-hand. The reference point used in utility evaluation is fixed at $R = 0$, so each season's profit is evaluated as a gain or a loss relative to the farmer's position at the start of the season. EC loans are single-period (each period's debt is fully cleared before the next period begins), so outstanding EC principal is not a state variable. The financial environment $z_t \in \{\text{None}, \text{Insurance}, \text{EC}\}$ is exogenous and known.

The farmer's only within-period choice is fertilizer $Q_{f,t} \geq 0$. The seed regime $(Q_{s,t}, Q_{dt,t})$ is scenario-fixed. Output depends on seed type and weather:

$$Y_t = \begin{cases} 0, & \varepsilon_t = \text{bad, local seeds} \quad \text{(crop failure)}, \\ g(\varepsilon_t)\, F_L(Q_{s,t}, Q_{f,t};\, \theta), & \varepsilon_t \in \{\text{mod}, \text{good}\},\ \text{local seeds}, \\ \bar{Y}_{DT}, & \varepsilon_t = \text{bad, DT seeds} \quad \text{(fixed floor: } \bar{Y}_{DT} = 50 \text{ kg)}, \\ g(\varepsilon_t)\, F_{DT}(Q_{dt,t}, Q_{f,t};\, \theta), & \varepsilon_t \in \{\text{mod}, \text{good}\},\ \text{DT seeds}, \end{cases}$$

where $g(\text{good}) = 0.95$ and $g(\text{moderate}) = 0.70$ scale the translog frontier in non-bad weather. In bad weather, output is determined structurally. Local seeds fail completely; DT seeds deliver a fixed drought-resistance floor. F_k is a translog production function under seed type $k \in \{L, DT\}$.

The translog technology for seed type k is

$$F_k(Q_k, Q_f;\, \theta) = A_k(Q_f) \exp\Big(\beta_k \ln Q_k + \beta_F\, \ell(Q_f) + \gamma_k (\ln Q_k)^2 + \gamma_F\, \ell(Q_f)^2 + \delta_{kF} \ln Q_k\, \ell(Q_f)\Big), \ell(Q_f) = \begin{cases} \ln Q_f \\ 0, \end{cases} \tag{17}$$

The scale factor $A_k(Q_f)$ takes one value at $Q_f = 0$ and another for $Q_f > 0$. Both are chosen so that output in good weather with 10 kg of seed matches the production function shown to farmers in Figure 4, which is 350 kg without fertilizer for both seed types, and 675 kg (local) and 950 kg (DT) at 50 kg of fertilizer. Output therefore jumps between zero and one kilogram of fertilizer, and the derivatives below apply at positive fertilizer levels. Diminishing marginal product of fertilizer is not implied by $\gamma_F < 0$ alone. Let

$$h_k(Q_f) \equiv \beta_F + 2\gamma_F \ln Q_f + \delta_{kF} \ln Q_k.$$

Then

$$\frac{\partial^2 F_k}{\partial Q_f^2} = \frac{F_k(Q_k, Q_f; \theta)}{Q_f^2} \left[h_k(Q_f)^2 - h_k(Q_f) + 2\gamma_F \right].$$

Thus fertilizer marginal product is declining on any domain where

$$h_k(Q_f)^2 - h_k(Q_f) + 2\gamma_F < 0.$$

Period profit, conditional on fertilizer choice Q_f, weather ε, and environment z_t, is

$$\Pi_t(\varepsilon;\, Q_f \mid g_t, z_t) = p_y\, Y_t - p_k Q_{k,t} - p_f Q_f - \phi_t(Q_f) + I_t(Q_f, \varepsilon) + L_t(Q_f, \varepsilon), \tag{18}$$

where p_y is the output price, p_k is the seed price, and p_f is the fertilizer price. The terms ϕ_t, I_t, L_t are contract-specific cash flows:

- **None**: $\phi_t \equiv I_t \equiv L_t \equiv 0$.
- **Insurance**: $\phi_t(Q_f) = \varphi\, p_f Q_f$ (premium); $I_t(Q_f, \varepsilon) = \delta\, p_f Q_f\, \mathbf{1}\{\varepsilon = \text{bad}\}$ (payout); $L_t \equiv 0$.
- **EC**: $\phi_t \equiv 0$; $I_t \equiv 0$; $L_t(Q_f, \varepsilon) = \kappa\, p_f Q_f\, \mathbf{1}\{\varepsilon = \text{bad}\}$ (loan inflow).

B.2 State Transitions and Budget Constraint

The feasible fertilizer set is

$$\mathcal{F}(s_t, z_t) = \Big\{ Q_f \geq 0 : p_f Q_f + \phi_t(Q_f) \leq W_t - p_k Q_{k,t} \Big\}.$$

Because the insurance premium is paid at the time of choice, the feasibility bound is tighter under Insurance than under None or EC.

Wealth evolves according to

$$W_{t+1} = W_t + \Pi_t(\varepsilon_t;\, Q_{f,t} \mid g_t, z_t) - (1 + r)\, L_t(Q_{f,t}, \varepsilon_t). \tag{19}$$

The wealth (19) deducts repayment of the EC loan, $(1+r)L_t$, from beginning-of-period-$(t+1)$ wealth. The farmer ends period t having received profit Π_t (which already includes the EC loan inflow L_t) and repays $(1 + r)L_t$ before period $t + 1$ begins. EC loans are single-period; for None and Insurance, $L_t \equiv 0$ and (19) reduces to $W_{t+1} = W_t + \Pi_t$. The reference point stays at $R = 0$ in every season.

B.3 Preferences: Cumulative Prospect Theory

Outcomes are evaluated relative to the reference point R_t. Define the gain/loss realization as

$$x_t(\varepsilon;\, Q_f) \equiv \Pi_t(\varepsilon;\, Q_f \mid g_t, z_t) - R_t.$$

The value function is kinked at zero:

$$v(x;\, \sigma, \lambda) = \begin{cases} x^{\sigma}, & x \geq 0, \\ -\lambda(-x)^{\sigma}, & x < 0, \end{cases} \qquad \sigma \in (0, 1],\ \lambda \geq 1. \tag{20}$$

Probabilities are distorted via the Prelec (Prelec, 1998) weighting function $w(p; \alpha) = \exp\{-(-\ln p)^{\alpha}\}$, $\alpha > 0$. When $\alpha = 1$, there is no distortion (expected utility). When $\alpha < 1$, the function is inverse-S shaped, overweighting small probabilities. When $\alpha > 1$, the function is S-shaped, underweighting small probabilities. The sample mean estimate from Section 3 is $\hat{\alpha} = 1.198 > 1$, implying mild S-shaped weighting in this population. Decision weights are rank-dependent cumulative transforms of w, not raw Prelec weights at marginal probabilities. Following the standard CPT construction and the elicitation in Section 3, losses are weighted cumulatively from the worst outcome and gains from the best outcome. With $R = 0$, bad weather is a loss and moderate and good weather are gains at every fertilizer level in every environment, so the decision weights are

$$\begin{aligned} \omega(\text{bad}) &= w(p_{\text{bad}}; \alpha), \\ \omega(\text{moderate}) &= w(p_{\text{mod}} + p_{\text{good}}; \alpha) - w(p_{\text{good}}; \alpha), \\ \omega(\text{good}) &= w(p_{\text{good}}; \alpha). \end{aligned}$$

At $\hat{\alpha} = 1.198$ these are 0.287, 0.341, and 0.406. Gain and loss weights are computed separately and need not sum to one.

B.4 Bellman Equation

Let $V_t(s_t)$ denote the value function. The farmer solves:

$$V_t(s_t) = \max_{Q_f \in \mathcal{F}(s_t, z_t)} \Bigg\{ \underbrace{\sum_{\varepsilon} \omega(\varepsilon; \alpha)\, v\big(\Pi_t(\varepsilon;\, Q_f \mid g_t, z_t) - R_t\big)}_{\text{CPT evaluation of weather risk}} + \beta \underbrace{\sum_{\varepsilon} p_{\varepsilon}\, V_{t+1}\big(\mathcal{T}(s_t, Q_f, \varepsilon, z_t)\big)}_{\text{continuation value (objective probabilities)}} \Bigg\}, \tag{21}$$

with terminal condition $V_{T+1}(\cdot) = 0$ and state transition $\mathcal{T}(s_t, Q_f, \varepsilon, z_t) \equiv W_{t+1}$ defined by (19). The first term uses CPT decision weights for within-period evaluation; the continuation value uses objective probabilities p_ε. CPT is applied only to the within-period weather lottery; farmers evaluate each season's gamble separately rather than integrating it with lifetime wealth. The reference point is fixed at $R = 0$. Letting it update to realized profit would raise the next reference point whenever today's investment pays off, so later outcomes would register as losses and optimal investment would collapse toward zero. Because R is fixed, wealth affects the farmer only through the budget for fertilizer in later seasons. The horizon is $T = 5$ seasons, and $T = 4$, the number of seasons played in each environment, gives the same first-season policy. The intertemporal discount factor is $\beta = 0.95$. Starting wealth is the game endowment of 5,000 KES.

C. Closed-Form Benchmark Results

C.1 Technology Derivative

Differentiating (17) with respect to Q_f at $Q_f > 0$, where A_k is constant and $\frac{d}{dQ_f} \ln Q_f = \frac{1}{Q_f}$, gives

$$\boxed{\frac{\partial F_k(Q_k, Q_f;\, \theta)}{\partial Q_f} = \frac{F_k(Q_k, Q_f;\, \theta)}{Q_f}\Big(\beta_F + 2\gamma_F \ln Q_f + \delta_{kF} \ln Q_k\Big).} \tag{22}$$

Let

$$h_k(Q_f) \equiv \beta_F + 2\gamma_F \ln Q_f + \delta_{kF} \ln Q_k.$$

Then

$$\frac{\partial^2 F_k}{\partial Q_f^2} = \frac{F_k(Q_k, Q_f; \theta)}{Q_f^2}\left[h_k(Q_f)^2 - h_k(Q_f) + 2\gamma_F\right].$$

Therefore the marginal product of fertilizer is declining only when

$$h_k(Q_f)^2 - h_k(Q_f) + 2\gamma_F < 0$$

on the relevant domain. The condition $\gamma_F < 0$ alone is not sufficient. Define the expected marginal revenue product (EMRP), which averages only over non-bad weather states because bad-weather output is structurally constant (zero for local seeds, $\bar{Y}_{DT}$ for DT seeds) and therefore carries zero marginal product of fertilizer:

$$\mathrm{EMRP}_k(Q_f) \equiv p_y\, \bar{g}\, \frac{\partial F_k(Q_k, Q_f;\, \theta)}{\partial Q_f}, \qquad \bar{g} \equiv p_{\mathrm{mod}}\, g(\mathrm{mod}) + p_{\mathrm{good}}\, g(\mathrm{good}). \tag{23}$$

At calibrated values, $\bar{g} = 0.3 \times 0.70 + 0.4 \times 0.95 = 0.590$. $\mathrm{EMRP}_k(\cdot)$ is strictly decreasing in Q_f on any domain where

$$h_k(Q_f)^2 - h_k(Q_f) + 2\gamma_F < 0.$$

C.2 Risk-Neutral First-Order Condition and Effective Marginal Costs

A risk-neutral farmer maximizes expected period profit. Differentiating with respect to Q_f and setting the derivative to zero at an interior optimum $Q_f^\star$:

$$\mathrm{EMRP}_k(Q_f^\star) = p_f^{\mathrm{eff}}. \tag{24}$$

The effective marginal cost p_f^{eff} is contract-specific and summarizes how each contract alters the expected cost of fertilizer:

Environment	Effective marginal cost p_f^{eff}	Feasibility bound $\bar{Q}_f$
None	p_f	$\dfrac{W_t - p_k Q_k}{p_f}$
Insurance	$p_f\big[(1+\varphi) - \delta\, p_{\mathrm{bad}}\big]$	$\dfrac{W_t - p_k Q_k}{(1+\varphi)\, p_f}$
Emergency Credit	$p_f\big[1 - \kappa\, p_{\mathrm{bad}}\big]$	$\dfrac{W_t - p_k Q_k}{p_f}$

Notes: W_t denotes cash-on-hand. $p_k Q_k$ denotes the scenario-fixed seed cost. The feasibility bound is the maximum feasible fertilizer given cash-on-hand. Repayment of EC principal enters through the continuation value, not the within-period constraint.

Because $\mathrm{EMRP}_k(\cdot)$ is decreasing, fertilizer demand is higher when p_f^{eff} is lower:

$$Q_f^{\star,a} > Q_f^{\star,b} \quad \Longleftrightarrow \quad p_f^{\mathrm{eff},a} < p_f^{\mathrm{eff},b}. \tag{25}$$

At calibrated values ($\delta = 0.80$, $\varphi = 0.24$, $p_{\mathrm{bad}} = 0.30$, $\kappa = 1$, $p_f = 120$):

$$\begin{aligned} p_f^{\mathrm{eff,None}} &= 120, \\ p_f^{\mathrm{eff,Ins}} &= 120 \times [1.24 - 0.24] = 120 \quad (\delta\, p_{\mathrm{bad}} = 0.24 = \varphi \text{ exactly}), \\ p_f^{\mathrm{eff,EC}} &= 120 \times [1 - 0.30] = 84. \end{aligned}$$

Insurance is actuarially neutral with respect to fertilizer cost at calibration. The premium exactly equals the expected payout per unit of fertilizer. The risk-neutral interior ranking is therefore $Q_f^{\star,\mathrm{EC}} > Q_f^{\star,\mathrm{None}} = Q_f^{\star,\mathrm{Ins}}$, and all differential predictions between Insurance and

None arise through CPT channels, not through effective marginal costs.

This yields the interior fertilizer ranking:

- **EC vs. None**: EC unambiguously lowers the effective marginal cost ($p_f^{\text{eff,EC}} = 84 < 120$), so $Q_f^{\star,\text{EC}} > Q_f^{\star,\text{None}}$ at interior solutions.
- **Insurance vs. None**: Identical at calibration ($p_f^{\text{eff,Ins}} = p_f^{\text{eff,None}} = 120$). The Insurance-None difference in realized investment operates through CPT, specifically through the loss-aversion reduction channel (Proposition 3).
- **Liquidity**: Insurance uniquely tightens the feasibility bound at the choice stage, so binding constraints may reduce realized fertilizer below the interior prediction even when effective marginal costs are equal.

Caveat on EC welfare. The within-period ranking $Q_f^{\star,\text{EC}} > Q_f^{\star,\text{None}}$ does not imply that EC dominates in welfare terms. EC loan disbursement boosts within-period profit and fertilizer incentives, but future repayment $(1+r)L_t$ reduces continuation-value wealth W_{t+1}. Whether EC raises expected lifetime utility depends on the full dynamic program and is sensitive to r and β. The rankings above are within-period. In the calibrated dynamic model at the 5,000 KES endowment, the risk-neutral optimum is 13 kg under local seeds, 14 kg under local + insurance, and 13 kg under local + EC, because the budget constraint binds in later seasons and the EC repayment draws on next-season wealth.

D. CPT Optimality Conditions

D.1 CPT First-Order Condition

Fix a period t and suppress subscripts. The CPT objective is

$$\mathcal{U}(Q_f;\, \sigma, \lambda, \alpha) = \sum_{\varepsilon} \omega(\varepsilon;\alpha)\, v\big(\Pi(\varepsilon;\, Q_f) - R\big).$$

Differentiating with respect to Q_f and applying the chain rule:

$$\frac{\partial \mathcal{U}}{\partial Q_f} = \sum_{\varepsilon} \omega(\varepsilon;\alpha)\, v'\big(x_\varepsilon(Q_f)\big)\, \Pi_f(\varepsilon;\, Q_f), \qquad \Pi_f(\varepsilon;\, Q_f) \equiv \frac{\partial \Pi(\varepsilon;\, Q_f)}{\partial Q_f}.$$

At an interior optimum the first-order condition (FOC) is

$$\Phi(Q_f^\star) \equiv \sum_{\varepsilon} \omega(\varepsilon;\alpha)\, v'\big(x_\varepsilon(Q_f^\star)\big)\, \Pi_f(\varepsilon;\, Q_f^\star) = 0. \tag{26}$$

The value function derivative is

$$v'(x;\,\sigma,\lambda) = \begin{cases} \sigma\, x^{\sigma-1}, & x > 0, \\ \lambda\,\sigma\,(-x)^{\sigma-1}, & x < 0. \end{cases} \tag{27}$$

Note that $v'(0)$ is undefined for $\sigma < 1$; the FOC uses $v'(x_\varepsilon(Q_f^\star))$ and requires $x_\varepsilon(Q_f^\star) \neq 0$ for all ε, which holds generically. The EU special case obtains when $\sigma = \lambda = 1$ and $\alpha = 1$, giving $v'(x) = 1$ and $\omega(\varepsilon;\alpha) = p_\varepsilon$, so (26) reduces to $\mathrm{EMRP}_k(Q_f^\star) = p_f^{\text{eff}}$.

Remark 1 (CPT reduces to risk-neutral EUT) *Setting $\sigma = \lambda = 1$, $\alpha = 1$, $R = 0$ renders the CPT value function linear ($v(x) = x$ for all x) and the decision weights equal to objective probabilities ($\omega(\varepsilon;\alpha) = p_\varepsilon$). The CPT Bellman objective then becomes $\sum_\varepsilon p_\varepsilon\big[\Pi_\varepsilon + \beta\, V_{t+1}(W_{t+1,\varepsilon})\big]$. The EUT solver with $\gamma = 0$ (linear CRRA, $u(\omega) = \omega$) maximizes $\sum_\varepsilon p_\varepsilon\big[W_{t+1,\varepsilon} + \beta\, V_{t+1}(W_{t+1,\varepsilon})\big]$. Since $W_{t+1,\varepsilon} = W_t + \Pi_\varepsilon - d_\varepsilon$ (where d_ε is EC repayment), the two objectives differ by the constant W_t and the term $\sum_\varepsilon p_\varepsilon\, d_\varepsilon$.*

*For **local seeds**, **local + insurance**, and **DT seeds**, $d_\varepsilon = 0$ for all ε, so both objectives share the same* $\arg\max$ *and produce identical optimal fertilizer. For **local + EC**, repayment $(1+r)\kappa p_f Q_f$ in bad weather enters the EUT within-period objective but only the CPT continuation value; EUT($\gamma = 0$) therefore imposes an additional effective per-unit cost of $p_{\text{bad}}(1+r)\kappa p_f$ on fertilizer that CPT(degenerate) does not see within the period. As a result, CPT gives weakly higher $Q^\star$ than EUT under local + EC. Backward-induction simulations confirm both predictions. Local seeds, local + insurance, and DT seeds $Q^\star$ values agree to within grid tolerance; the local + EC $Q^\star$ under CPT(degenerate) weakly exceeds the EUT($\gamma = 0$) value.*

Define the *loss set* and *gain set* at choice Q_f:

$$\mathcal{L}(Q_f) \equiv \big\{\varepsilon : x_\varepsilon(Q_f) < 0\big\}, \qquad \mathcal{G}(Q_f) \equiv \big\{\varepsilon : x_\varepsilon(Q_f) \geq 0\big\}. \tag{28}$$

Remark 2 (When moderate weather falls in the loss set) *Whether moderate weather lies in the loss set depends on the profit level $\Pi(\text{mod};\, Q_f^\star)$ relative to the reference point R. For financial contract z:*

$$\text{mod} \in \mathcal{L}(Q_f^\star) \quad \Longleftrightarrow \quad p_y\, g(\text{mod})\, F_k(Q_k, Q_f^\star) - p_k Q_k - p_f^{\text{eff}}\, Q_f^\star < R.$$

The condition becomes easier to satisfy as R increases and depends on the realized $Q_f^\star$ through both the revenue term and the cost term. With $R = 0$ and calibrated parameters, moderate-weather profit is positive at every fertilizer level in every environment (at least 13,800 KES), so moderate weather is never a loss state and the loss set is $\mathcal{L}(Q_f) = \{\text{bad}\}$ throughout. The

results below that allow moderate weather in the loss set apply only under a higher reference point.

D.2 Contract-Specific Marginal Profit

The marginal profit of fertilizer differs across financial environments. For non-bad weather states ($\varepsilon \in \{\text{mod}, \text{good}\}$), output responds to fertilizer through the translog:

$$\Pi_f^{\text{None}}(\varepsilon;\, Q_f) = p_y\, g(\varepsilon)\, F_f(Q_f) - p_f, \tag{29}$$

$$\Pi_f^{\text{Ins}}(\varepsilon;\, Q_f) = p_y\, g(\varepsilon)\, F_f(Q_f) - p_f(1+\varphi) + \delta\, p_f\, \mathbf{1}\{\varepsilon = \text{bad}\}, \tag{30}$$

$$\Pi_f^{\text{EC}}(\varepsilon;\, Q_f) = p_y\, g(\varepsilon)\, F_f(Q_f) - p_f + \kappa\, p_f\, \mathbf{1}\{\varepsilon = \text{bad}\}, \tag{31}$$

where $F_f(Q_f) \equiv \partial F_k / \partial Q_f$ is given by (22). In bad weather, output is structurally constant (zero for local seeds; $\bar{Y}_{DT}$ for DT seeds), so $\partial Y / \partial Q_f = 0$ and the $p_y g(\varepsilon) F_f$ terms above vanish:

$$\begin{aligned}
\Pi_f^{\text{None}}(\text{bad};\, Q_f) &= -p_f, \\
\Pi_f^{\text{Ins}}(\text{bad};\, Q_f) &= p_f(\delta - 1 - \varphi), \\
\Pi_f^{\text{EC}}(\text{bad};\, Q_f) &= p_f(\kappa - 1).
\end{aligned}$$

At $\kappa = 1$, $\Pi_f^{\text{EC}}(\text{bad};\, Q_f) = 0$. The bad-weather marginal profit under EC is exactly zero, a key structural result for the comparative statics below.

D.3 Implicit Function Theorem Framework

For any scalar parameter θ (e.g., λ, σ, α, φ, δ, κ), define $\Phi_\theta \equiv \partial\Phi/\partial\theta$ and $\Phi_{Q_f} \equiv \partial\Phi/\partial Q_f$. The implicit function theorem applied to (26) yields

$$\frac{dQ_f^\star}{d\theta} = -\frac{\Phi_\theta(Q_f^\star;\, \theta)}{\Phi_{Q_f}(Q_f^\star;\, \theta)}. \tag{32}$$

The second-order condition (SOC) at an interior maximum requires $\Phi_{Q_f}(Q_f^\star) < 0$. This is maintained as a local second-order condition. In the risk-neutral benchmark, a declining EMRP schedule requires

$$h_k(Q_f)^2 - h_k(Q_f) + 2\gamma_F < 0$$

on the relevant domain. Under CPT, $\Phi_{Q_f} < 0$ is not guaranteed by technology curvature alone because the value-function curvature and the gain–loss kink also enter the objective.

We therefore impose $\Phi_{Q_f}(Q_f^\star) < 0$ at the interior optimum and verify uniqueness numerically in the calibrated model. The CPT decision weights also assume profit outcomes are ranked bad $\leq$ moderate $\leq$ good for all $Q_f \in \mathcal{F}(s_t, z_t)$. This holds because $g(\text{mod}) < g(\text{good})$ and bad-weather output lies below the translog frontier at any $Q_f > 0$ (the output-ranking condition: $g(\text{bad}) = 0$ for local seeds; $0 < g(\text{bad}) < g(\text{mod}) < g(\text{good})$ for DT seeds). Under the SOC, $\text{sign}(dQ_f^\star/d\theta) = \text{sign}(\Phi_\theta(Q_f^\star;\, \theta))$.

Remark 3 (Closed-form SOC expression and the EC special case) *Differentiating* (26) *with respect to* Q_f *gives the closed-form expression*

$$\begin{aligned}\Phi_{Q_f} = &\sum_{\varepsilon\in\mathcal{G}} \omega(\varepsilon;\alpha)\Big[\sigma(\sigma-1)\, x_\varepsilon^{\sigma-2}\left(\Pi_f(\varepsilon)\right)^2 + \sigma\, x_\varepsilon^{\sigma-1}\,\Pi_{ff}(\varepsilon)\Big] \\ &+ \sum_{\varepsilon\in\mathcal{L}} \omega(\varepsilon;\alpha)\Big[-\lambda\sigma(\sigma-1)\,(-x_\varepsilon)^{\sigma-2}\left(\Pi_f(\varepsilon)\right)^2 + \lambda\sigma\,(-x_\varepsilon)^{\sigma-1}\,\Pi_{ff}(\varepsilon)\Big],\end{aligned} \tag{33}$$

where $\Pi_{ff}(\varepsilon) \equiv \partial^2\Pi/\partial Q_f^2$. *For gain states* ($\varepsilon \in \mathcal{G}$), *the first bracketed term contributes negatively to* Φ_{Q_f} *when* $\sigma < 1$ *(since* $\sigma - 1 < 0$*). For loss states* ($\varepsilon \in \mathcal{L}$), *the first bracketed term contributes positively when* $\sigma < 1$ *and* $\lambda \geq 1$ *(since* $-\lambda(\sigma-1) > 0$*). This CPT convexity-in-losses channel prevents* (33) *from being signed analytically under None and Insurance: the positive loss-state contribution competes with the negative gain-state contributions, and the net sign depends on magnitudes at* $Q_f^\star$ *rather than structural properties of the environment.*

Under EC with $\kappa = 1$, *the zero-marginal-product result* $\Pi_f^{\text{EC}}(\text{bad}) = 0$ *carries through to the SOC. Bad-weather output for local seeds is identically zero at all* Q_f, *so* $\Pi_{ff}^{\text{EC}}(\text{bad}) = 0$ *as well. Both terms in the bad-weather summand of* (33) *are therefore zero, and bad weather does not enter* $\Phi_{Q_f}^{\text{EC}}$. *When moderate and good weather lie in the gain set,* (33) *reduces to a sum over* $\varepsilon \in \{\text{mod}, \text{good}\}$ *in which both components of each term are negative (the first by gain-state concavity, the second by diminishing marginal product of fertilizer in non-bad states). The SOC* $\Phi_{Q_f}^{\text{EC}} < 0$ *therefore holds analytically under EC, provided bad weather is the only loss state and fertilizer exhibits diminishing marginal product in non-bad states. The same zero-marginal-product channel that eliminates the loss-aversion effect on fertilizer under EC also eliminates the CPT obstruction to formally establishing the SOC.*

All comparative statics below follow this template. Compute Φ_θ, determine its sign under stated conditions, and apply (32).

Remark 4 (Static approximation and dynamic validation) *The comparative statics in Section E are derived from the within-period first-order condition* $\Phi_{\text{static}}(Q_f^\star, \theta) = 0$, *which is the exact FOC for period* T *(where* $V_{T+1} \equiv 0$*) and a static approximation for* $t < T$. *The*

full dynamic FOC for $t < T$ adds a continuation-value term:

$$\Phi_{\text{static}}(Q_f^\star, \theta) + \beta \sum_{\varepsilon} p_\varepsilon \frac{\partial V_{t+1}\big(\mathcal{T}(s_t, Q_f^\star, \varepsilon, z_t)\big)}{\partial Q_f} = 0.$$

This term is nonzero in general because Q_f affects W_{t+1} through current-period profit and the EC repayment. With R fixed, W_{t+1} matters only through the budget for fertilizer in later seasons, so the term vanishes whenever that budget does not bind. The cross-partials $\partial^2 V_{t+1}/\partial Q_f \partial\theta$ are not analytically tractable when it does. The sign predictions from Φ_{static} are validated in the full dynamic program by backward induction at the calibrated parameters for $\lambda \in [1, 5]$ (Figure A2).

Remark 5 (Corner solutions) *The IFT formula (32) applies at interior optima ($Q_f^\star > 0$ and $Q_f^\star < \bar{Q}_f$). Corner solutions at $Q_f^\star = 0$ arise when $\Phi(0, \theta) \leq 0$. The CPT marginal value of the first unit of fertilizer is non-positive. Under high loss aversion and when bad weather is in the loss set, the loss-state disutility can dominate the gain-state benefit at all $Q_f \geq 0$, pushing the optimum to the zero corner. Higher λ expands the parameter region where $Q_f^\star = 0$.*

E. Comparative Statics: Propositions

E.1 Loss Aversion λ

Since λ enters only through $v'(x)$ for $x < 0$ (equation (27)), differentiating (26) with respect to λ:

$$\Phi_\lambda(Q_f) = \sum_{\varepsilon \in \mathcal{L}(Q_f)} \omega(\varepsilon; \alpha)\, \sigma\left(-x_\varepsilon(Q_f)\right)^{\sigma-1} \Pi_f(\varepsilon;\, Q_f). \tag{34}$$

Expression (34) shows that λ affects fertilizer choice *only through loss states*. If the loss set $\mathcal{L}(Q_f^\star)$ is empty, then $\Phi_\lambda = 0$ and $dQ_f^\star/d\lambda = 0$. Otherwise, the sign is determined by whether fertilizer has positive or negative marginal profit in loss states. Because bad weather is the only loss state at calibrated values, Φ_λ consists of the bad-weather term alone, and its sign is the sign of $\Pi_f(\text{bad})$. The predictions by environment are

Environment	$\Pi_f(\text{bad};\, Q_f^\star)$	Sign of Φ_λ	$dQ_f^\star/d\lambda$
Local seeds	-120 KES	Negative	Negative
Local + insurance	-52.8 KES	Negative (smaller)	Negative (slightly smaller)
Local + EC	0 KES	Zero	Zero
DT seeds	-120 KES	Negative	Negative

Notes. Calibrated values are $p_f = 120$, $\delta = 0.80$, $\varphi = 0.24$, and $\kappa = 1$. The signs follow from $\Pi_f(\text{bad})$ and the second-order condition. The EC entry is exact (Proposition 2). Under local + insurance the numerator Φ_λ is smaller than under local seeds, but the full comparative static also depends on Φ_{Q_f}, which is smaller as well, so the size comparison comes from the numerical solution, -1.25 kg per unit of λ against -1.5 under local seeds. The size of the DT effect depends on starting wealth (Section F).

Remark 6 (Moderate-weather increasing channel under Insurance) *This case does not arise at calibrated values with $R = 0$, where moderate weather is always a gain. When moderate weather lies in the loss set (*$\text{mod} \in \mathcal{L}(Q_f^\star)$*), the moderate-weather terms in $\Phi_\lambda^{\text{Ins}}$ and $\Phi_\lambda^{\text{None}}$ are* not *identical. The Insurance effective cost of fertilizer is $p_f(1+\varphi)$ rather than p_f, so:*

$$\Pi_f^{\text{Ins}}(\text{mod};\, Q_f^\star) = p_y\, g(\text{mod})\, F_f(Q_f^\star) - p_f(1+\varphi) < p_y\, g(\text{mod})\, F_f(Q_f^\star) - p_f = \Pi_f^{\text{None}}(\text{mod};\, Q_f^\star).$$

The Insurance moderate-weather marginal profit is more negative by $\varphi\, p_f = 0.24 \times 120 = 28.8$ KES. Since $\Pi_f^{\text{Ins}}(\text{mod}) < \Pi_f^{\text{None}}(\text{mod}) < 0$ when moderate lies in the loss set, the moderate-weather term in $|\Phi_\lambda^{\text{Ins}}|$ exceeds the corresponding term in $|\Phi_\lambda^{\text{None}}|$. This increasing channel *counteracts the bad-weather reduction (where $|\Pi_f^{\text{Ins}}(\text{bad})| < |\Pi_f^{\text{None}}(\text{bad})|$), so the net comparison $|\Phi_\lambda^{\text{Ins}}|$ vs. $|\Phi_\lambda^{\text{None}}|$ becomes ambiguous when moderate lies in the loss set. The table ranking $|dQ_f^\star/d\lambda|_{\text{Ins}} \le |dQ_f^\star/d\lambda|_{\text{None}}$ therefore holds when moderate weather is not in the loss set, or is confirmed numerically via backward induction when it is.*

Proposition 1 (Loss aversion suppresses fertilizer without a financial contract) *Suppose $z_t = \text{None}$. If fertilizer has non-positive marginal profit in every loss state at the optimum,*

$$\Pi_f^{\text{None}}(\varepsilon;\, Q_f^\star) \le 0 \quad \textit{for all } \varepsilon \in \mathcal{L}(Q_f^\star),$$

then $dQ_f^\star/d\lambda \le 0$. Higher loss aversion weakly reduces optimal fertilizer.

Proof. From (34), every term in $\Phi_\lambda(Q_f^\star)$ is the product of $\omega(\varepsilon;\alpha) > 0$, $\sigma(-x_\varepsilon)^{\sigma-1} > 0$, and $\Pi_f^{\text{None}}(\varepsilon;\, Q_f^\star) \le 0$ by assumption. Hence $\Phi_\lambda(Q_f^\star) \le 0$. Since $\Phi_{Q_f} < 0$, equation (32) gives $dQ_f^\star/d\lambda \le 0$. ■

Remark 7 *For local seeds, bad-weather output is structurally zero (crop failure), so* $\Pi_f^{\text{None}}(\text{bad};\, Q_f^\star) = -p_f = -120$ *KES regardless of the fertilizer level. Thus the condition of the Proposition is satisfied mechanically for any interior optimum under local seeds. Bad weather is always in the loss set (since* $\Pi^{\text{None}}(\text{bad};\, Q_f^\star) < 0 \le R$ *at moderate fertilizer levels), and the bad-weather term in* Φ_λ *is always negative. If moderate weather also lies in the loss set (when* R *is high), the condition requires* $p_y\, g(\text{mod})\, F_f(Q_f^\star) < p_f$*, i.e., moderate-weather marginal revenue is below the fertilizer price. At calibrated values, the risk-neutral FOC sets* $p_y\, \bar{g}\, F_f(Q_f^\star) = p_f$*, and since* $\bar{g} > g(\text{mod})$*, the moderate-weather condition is formally satisfied at the risk-neutral benchmark. In practice, moderate weather rarely falls into the loss set at calibrated parameter values.*

Proposition 2 (EC reduces or eliminates the loss-aversion effect) *Suppose* $z_t = \text{EC}$*,* $\kappa = 1$*, and local seeds.*

(a) Bad-weather term always zero. *Because bad-weather output is structurally zero (crop failure),* $\partial Y/\partial Q_f = 0$ *in bad weather, and:*

$$\Pi_f^{\text{EC}}(\text{bad};\, Q_f) = 0 - p_f + \kappa\, p_f = p_f(\kappa - 1) = 0.$$

The bad-weather summand in Φ_λ *is* $\omega(\text{bad};\alpha)\, \sigma(-x_{\text{bad}})^{\sigma-1} \cdot 0 = 0$*, regardless of whether* $\text{bad} \in \mathcal{L}(Q_f^\star)$ *and regardless of the reference point* R*.*

(b) Full elimination. *If bad weather is the only loss state (*$\mathcal{L}(Q_f^\star) = \{\text{bad}\}$*), then* $\Phi_\lambda = 0$ *and* $dQ_f^\star/d\lambda = 0$*. Loss aversion is irrelevant to fertilizer choice.*

(c) General reduction. *If moderate weather also lies in the loss set,* Φ_λ^{EC} *equals the moderate-weather term only (bad-weather term remains zero). Note that* $\Pi_f^{\text{EC}}(\text{mod}) = p_y g(\text{mod}) F_f - p_f = \Pi_f^{\text{None}}(\text{mod})$*. EC does not change the moderate-weather marginal profit. Therefore* $|\Phi_\lambda^{\text{EC}}| < |\Phi_\lambda^{\text{None}}|$ *strictly whenever bad weather is in the loss set under None (the bad-weather term contributes* $\omega(\text{bad};\alpha)\, \sigma(-x_{\text{bad}})^{\sigma-1}(-p_f) < 0$ *to* $\Phi_\lambda^{\text{None}}$ *but exactly zero to* Φ_λ^{EC}*). At calibrated values bad weather is the only loss state, so Part (b) applies, and the backward-induction solution gives* $dQ_f^\star/d\lambda = 0$ *across* $\lambda \in [1, 5]$ *(Figure A2).*

Proof. Part (a): With $\kappa = 1$, the EC loan exactly covers the fertilizer cost in bad weather. Net marginal profit $= 0 - p_f + p_f = 0$. The bad-weather summand in (34) is zero whether or not bad weather lies in $\mathcal{L}(Q_f^\star)$.

Part (b): If $\mathcal{L}(Q_f^\star) = \{\text{bad}\}$, all summands in (34) are zero (bad-weather term by Part (a), gain-state terms by definition). Hence $\Phi_\lambda = 0$ and (32) gives $dQ_f^\star/d\lambda = 0$.

Part (c): With $\mathcal{L}(Q_f^\star) \supseteq \{\text{bad}, \text{mod}\}$, $\Phi_\lambda^{\text{EC}} = \omega(\text{mod};\alpha)\, \sigma(-x_{\text{mod}})^{\sigma-1}\, \Pi_f^{\text{EC}}(\text{mod};\, Q_f^\star)$ (bad-weather term $= 0$ by Part (a)). Since $\Pi_f^{\text{EC}}(\text{mod}) = p_y\, g(\text{mod})\, F_f - p_f = \Pi_f^{\text{None}}(\text{mod})$, the moderate-weather term is identical across regimes. Under None, $\Phi_\lambda^{\text{None}}$ additionally

includes $\omega(\text{bad};\alpha)\,\sigma(-x_{\text{bad}})^{\sigma-1}(-p_f) < 0$. Therefore $|\Phi_\lambda^{\text{EC}}| < |\Phi_\lambda^{\text{None}}|$: the numerator of the IFT comparative static is strictly reduced under EC. A strict ordering of the full comparative statics,

$$\left|\frac{dQ_f^\star}{d\lambda}\right|_{\text{EC}} < \left|\frac{dQ_f^\star}{d\lambda}\right|_{\text{None}},$$

also requires comparable local curvature terms $|\Phi_{Q_f}^{\text{EC}}|$ and $|\Phi_{Q_f}^{\text{None}}|$, or must be verified numerically. ■

Remark 8 *The mechanism is zero bad-weather marginal profit under EC, not an empty-loss-set argument. EC with $\kappa = 1$ offsets fertilizer costs in bad weather, making the bad-weather marginal profit zero regardless of whether the bad-weather profit level lies above or below R. Under DT seeds, bad-weather output is also a fixed constant ($\bar{Y}_{DT} = 50$), so $\Pi_f^{\text{EC,DT}}(\text{bad}) = 0 - p_f + p_f = 0$ at $\kappa = 1$ and the same mechanism applies.*

Proposition 3 (Insurance reduces but need not eliminate the loss-aversion effect) *Suppose $z_t =$ Insurance. For local seeds, bad-weather output is zero, so the bad-state marginal profit under insurance is*

$$\Pi_f^{\text{Ins}}(\text{bad};\, Q_f) = p_f(\delta - 1 - \varphi).$$

Maintained condition: $\delta < 1+\varphi$ *(at calibration, $1+\varphi-\delta = 0.44 > 0$). Under this condition, $\Pi^{\text{Ins}}(\text{bad};\, Q_f) < 0$ for all $Q_f > 0$, so* bad $\in \mathcal{L}(Q_f^\star)$ *unconditionally (for any $R \geq 0$). If $\delta > 1 + \varphi$, then $\Pi_f^{\text{Ins}}(\text{bad};\, Q_f^\star) > 0$. In that case, bad-weather terms in Φ_λ contribute positively, weakening or reversing the negative λ effect. At calibrated values ($\delta = 0.80$, $\varphi = 0.24$), $\delta - 1 - \varphi = -0.44 < 0$, so the bad-weather term remains negative and the λ effect persists (reduced relative to the local seeds case, since $|\delta - 1 - \varphi| < 1$).*

Proof. Since bad-weather output is zero for local seeds, $\partial Y_{\text{bad}}/\partial Q_f = 0$. Substituting: $\Pi_f^{\text{Ins}}(\text{bad};\, Q_f) = 0 - p_f(1+\varphi) + \delta\, p_f = p_f(\delta - 1 - \varphi)$. The bad-weather term in Φ_λ has sign equal to $\text{sign}(\delta - 1 - \varphi)$, which is negative at calibrated values ($\delta - 1 - \varphi = -0.44$). *Reduction through bad-weather channel:* Comparing with local seeds, $|\Pi_f^{\text{Ins}}(\text{bad})| = 0.44\, p_f < p_f = |\Pi_f^{\text{None}}(\text{bad})|$, so the bad-weather contribution to $|\Phi_\lambda^{\text{Ins}}|$ is strictly smaller than to $|\Phi_\lambda^{\text{None}}|$. *Caveat on moderate-weather raising:* If moderate weather lies in the loss set, $\Pi_f^{\text{Ins}}(\text{mod}) = p_y g(\text{mod}) F_f - p_f(1+\varphi)$ is more negative than $\Pi_f^{\text{None}}(\text{mod}) = p_y g(\text{mod}) F_f - p_f$ by $\varphi\, p_f = 28.8$ KES. This increasing channel counteracts the bad-weather reduction; the net ordering $|\Phi_\lambda^{\text{Ins}}| \leq |\Phi_\lambda^{\text{None}}|$ holds when moderate is not in the loss set, or is verified numerically when it is (see Remark 6). The smaller numerator does not by itself imply a smaller $|dQ_f^\star/d\lambda|$, because Φ_{Q_f} is also smaller in magnitude under insurance. At calibrated values the numerical solution gives -1.25 kg per unit of λ under local + insurance against -1.5 under local seeds.

■

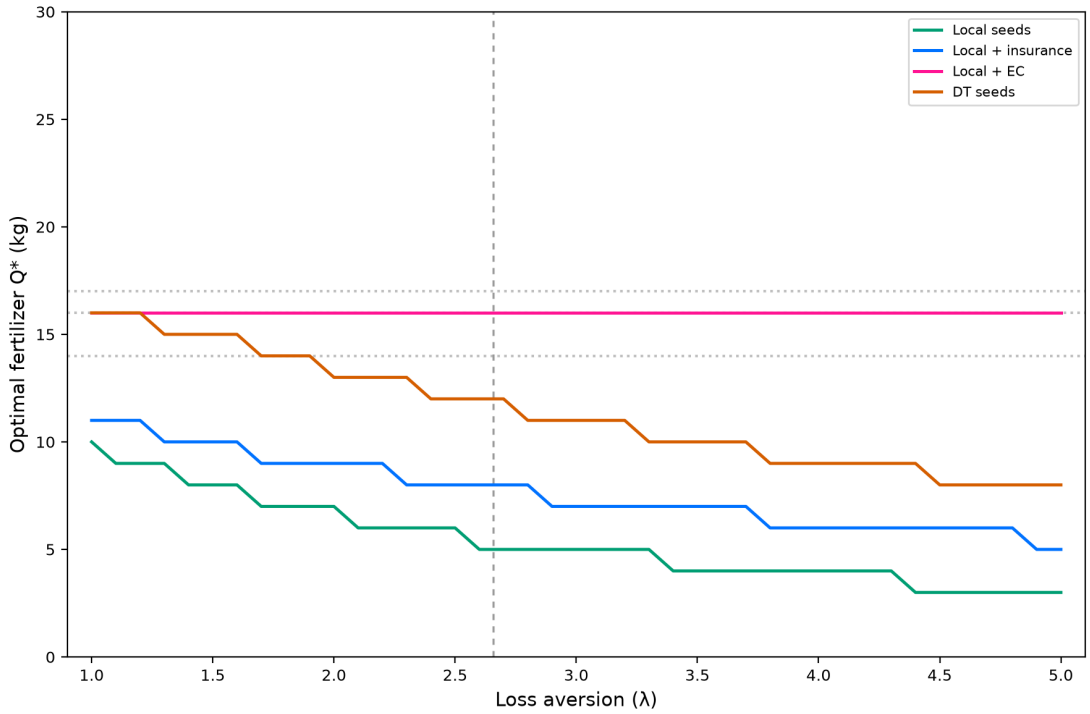


Figure A2: **BI model optimal fertilizer Q^* as a function of loss aversion λ.** *Note:* Each line shows the calibrated BI model prediction for one of the four environments, holding $\sigma = 0.572$ and $\alpha = 1.198$, with $R = 0$, first-season policy, and starting wealth $W_1 =$ 5,000 KES. *Green.* Local seeds (Proposition 1), $dQ^*/d\lambda < 0$, steepest decline. *Blue.* Local + insurance (Proposition 3), $dQ^*/d\lambda < 0$ and slightly flatter, because the payout returns part of the bad-weather fertilizer cost ($|\Pi_f^{\text{Ins}}(\text{bad})| < |\Pi_f^{\text{None}}(\text{bad})|$). *Pink.* Local + EC (Proposition 2), $dQ^*/d\lambda = 0$, because the EC loan covers the fertilizer cost in bad weather ($\kappa = 1$). *Orange.* DT seeds (Proposition 5), $dQ^*/d\lambda \leq 0$; see Section F. Dotted horizontal lines show the risk-neutral benchmark ($\sigma = \lambda = \alpha = 1$), which is 13 kg for local seeds, 14 kg for local + insurance, and 13 kg for local + EC. The local + EC line coincides with its benchmark across all λ, as Proposition 2 implies. The gap between any other line and its benchmark reflects curvature and probability weighting (σ, α), which are already active at $\lambda = 1$, and loss aversion widens it as λ increases. The vertical dashed line marks the estimated sample mean $\hat{\lambda} = 2.64$.

Category	Mechanism	$dQ_f^\star/d\sigma$
None	Gain-state upweighting dominates; bad-state negative term partially offsets	Positive
Insurance	Prem. raises p_f^{eff}; both positive	Positive
EC	Bad-state term = 0; gain-state dominance unambiguous	Positive (unambiguous)

Notes: Under maintained condition $(1+\sigma \ln x_\varepsilon) > 0$ for all gain states (satisfied at calibrated σ). EC has the most unambiguous sign since the zero bad-state term removes the only possible negative contribution to Φ_σ; the magnitude ranking across categories is not established without additional assumptions.

E.2 Diminishing Sensitivity σ

Since σ enters through both $v'(x)$ for gains and losses, differentiating (26) with respect to σ:

$$\Phi_\sigma(Q_f) = \sum_{\varepsilon \in \mathcal{G}(Q_f)} \omega(\varepsilon;\alpha)\, x_\varepsilon^{\sigma-1}\big(1+\sigma \ln x_\varepsilon\big)\, \Pi_f(\varepsilon;\, Q_f) + \lambda \sum_{\varepsilon \in \mathcal{L}(Q_f)} \omega(\varepsilon;\alpha)\, (-x_\varepsilon)^{\sigma-1}\big(1+\sigma \ln(-x_\varepsilon)\big)\, \Pi_f(\varepsilon;\, Q_f). \tag{35}$$

For realistic profit magnitudes exceeding $e^{-1/\sigma} \approx 0.17$ KES (at $\sigma = 0.572$), the factor $(1+\sigma \ln x_\varepsilon) > 0$ for all gain-state realizations, so when gain-state terms dominate, $\Phi_\sigma > 0$ and $dQ_f^\star/d\sigma > 0$.

Proposition 4 (Higher diminishing sensitivity increases fertilizer) *If $x_\varepsilon(Q_f^\star) > e^{-1/\sigma}$ for all $\varepsilon \in \mathcal{G}(Q_f^\star)$ and the gain-state contribution to (35) dominates, then $\Phi_\sigma > 0$ and $dQ_f^\star/d\sigma > 0$. A less concave value function leads to higher optimal fertilizer.*

Proof. The first condition ensures $(1+\sigma \ln x_\varepsilon) > 0$ for all gain-state realizations (satisfied at calibrated $\sigma = 0.572$ since $e^{-1/0.572} \approx 0.17$ KES is far below realistic profit magnitudes). This guarantees all gain-state terms in (35) are positive in sign. However, this alone does not establish that gain-state contributions *dominate* loss-state contributions in Φ_σ. That step is not available analytically under CPT. Dominance is therefore maintained as an additional assumption of the Proposition (the second stated condition). Given dominance, (32) gives $dQ_f^\star/d\sigma > 0$. ■

The model does not generate predictions for willingness to pay. Demand for insurance and emergency credit is analyzed empirically in Section 5.

F. Extension: Drought-Tolerant Seeds

The analysis above applies to local seeds. Under drought-tolerant (DT) seeds, replace $F_L(Q_{s,t}, Q_f;\, \theta)$ with $F_{DT}(Q_{dt,t}, Q_f;\, \theta)$ and p_L with p_{DT}. The optimization structure and effective marginal cost expressions are identical.

Two channels differentiate DT from local-seed outcomes:

- **Technology.** DT parameters $(\beta_{DT}, \gamma_{DT}, \delta_{DTF})$ shift the EMRP curve, changing the level of $Q_f^\star$ but not the signs of comparative statics.
- **Liquidity.** Higher seed cost ($p_{DT} > p_L$) tightens the feasibility bound $\bar{Q}_f = (W_t - p_{DT}\, Q_{dt,t})/p_f$, constraining the fertilizer budget independently of the interior optimum.

The loss aversion propositions hold for DT seeds under the same maintained condition, that bad weather lies in the loss set $\mathcal{L}(Q_f^\star)$, and this condition can fail for DT farmers. Quantitative predictions differ through EMRP levels and budget tightness, but the qualitative comparative statics are unchanged whenever the maintained condition holds.

Proposition 5 (Loss aversion suppresses fertilizer under DT seeds) *Suppose DT seeds and no financial contract. Because the bad-weather floor $\bar{Y}_{DT}$ does not depend on fertilizer, $\Pi_f^{\mathrm{DT}}(\text{bad};\, Q_f) = -p_f$. If bad weather lies in the loss set, then $dQ_f^\star/d\lambda \le 0$.*

Proof. The argument is identical to Proposition 1. Every term in Φ_λ is the product of a positive weight, a positive factor $\sigma(-x_\varepsilon)^{\sigma-1}$, and $\Pi_f^{\mathrm{DT}}(\text{bad}) = -p_f < 0$, so $\Phi_\lambda \le 0$, and (32) gives $dQ_f^\star/d\lambda \le 0$. ■

One notable difference applies to DT seeds. Bad-weather output is $\bar{Y}_{DT} = 50$ kg, generating bad-weather gross revenue $p_y \bar{Y}_{DT} = 3{,}750$ KES. Under no financial contract, bad-weather profit is $\Pi^{\mathrm{None,DT}}(\text{bad}) = 3{,}750 - p_{DT} Q_{dt} - p_f Q_f^\star$. Seeds are provided at no cost in the experimental game; $p_{DT} = 550$ KES is the market price of DT seeds, used as a calibration benchmark to evaluate whether bad-weather profit falls below the reference point under realistic field costs. At calibrated values ($p_{DT} = 550$ KES, $Q_{dt} = 10$), seed costs are $p_{DT} Q_{dt} = 5{,}500$ KES, so $\Pi^{\mathrm{None,DT}}(\text{bad}) = -1{,}750 - 120\, Q_f^\star < 0$ for all $Q_f^\star \ge 0$. Bad weather therefore lies in the loss set unconditionally under calibrated parameters, and the maintained condition of Proposition 5 is satisfied for DT seeds just as for local seeds. Because the seed cost exceeds the 5,000 KES game endowment, the size of the DT effect depends on the starting wealth assumed for DT seeds, while its sign does not. In settings with substantially lower DT seed costs, bad-weather profit could approach zero, its sign becoming reference-point sensitive, and the maintained condition could fail. When bad weather exits the loss set, Proposition 5 no longer holds. $\Phi_\lambda = 0$ even under None or Insurance, meaning λ does not suppress fertilizer investment. This occurs not through the EC zero-marginal-product mechanism but through absence of a loss state altogether. DT farmers in lower-seed-cost contexts may therefore exhibit reduced λ effects relative to local-seed farmers even without access to a financial instrument, and the reduction cannot be attributed to EC.