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Underconfidence and the low-experimentation trap

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We study how confidence bias affects investment in learning via experimentation, a mechanism critical for technology adoption under uncertainty. We hypothesize that bias direction and strength predict how willingness to experiment diverges from unbiased agents. We measure revealed and stated demand for experimenting with drought-resistant crop varieties of 1,957 farmers in West Africa, a climate change hotspot. Consistent with our hypothesis, confidence bias strongly predicts willingness to experiment. The effect, however, is driven exclusively by underconfident agents, among whom females are overrepresented. In deteriorating environments, this behavioral friction undercuts effective technology diffusion and risks trapping individuals in maladapted production environments.

JEL: D83, D91, O33, Q16, Q54, Q55
Keywords: Underconfidence; overconfidence; experimentation; adaptation.

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1. Introduction

Biased beliefs in one's abilities have economic consequences. Among the best documented consequences are the costs of overconfidence, that is, the costs of positively biased belief in one's abilities both in absolute (overestimation) and relative (overplacement) terms (Moore and Healy, 2008). Overconfidence has been linked to excess entry into markets (Camerer and Lovallo, 1999), excess trading on stock markets (Barber and Odean, 2000), excess asset acquisition (Malmendier and Tate, 2005), excess risk taking in agriculture (Barsbai et al., 2022), and reduced demand for information (Mesfin et al., 2023), among others.[1] These consequences carry substantial significance, not least because positive bias is widely regarded as empirically more prevalent in the population (Olsson, 2014) and as disproportionately affecting males (Barber and Odean, 2001).[2]

In a departure from the past literature's emphasis on overconfidence, we focus in the present paper on the economic consequences of confidence bias in general – and underconfidence in particular. This is motivated by the fact that surprisingly little is known about the negative part of the bias distribution, possibly because both underestimation of own abilities and underplacement relative to others are assumed to be less prevalent or to be insufficiently impactful.[3] As our paper shows, these assumptions are challenged by field evidence, both in absolute terms and relative to overconfidence.

In our field setting, individuals with varying beliefs in their own abilities need to decide about investment in learning via experimentation. The experimentation decision is not only critical for technology adoption under uncertainty, but also a context for which an existing literature supports hypotheses about the presence, direction, and magnitude of the effect of biased beliefs on decisions. Theory, for example, predicts that a positive confidence bias will lead to more, and a negative one to less,

[1]Benefits to overconfidence have also received attention. Bénabou and Tirole (2002) demonstrate the important motivational benefits of high self-confidence and the pitfalls of over-confidence. Johnson and Fowler (2011) and Gigerenzer et al. (2012) show that there can be evolutionary benefits to overconfidence, given the right ecological setting. Schwardmann and Van der Weele (2019) experimentally demonstrate the presence of strategic benefits from overconfidence in social interactions to boost persuasiveness.

[2]Benoît and Dubra (2011) and Olsson (2014) discuss the measurement issues associated with the supposed predominance of overconfidence in the population.

[3]In addition to later references, notable examples of papers that examine the full range of confidence bias and discuss the phenomenon of underconfidence in particular are Hoelzl and Rustichini (2005), Clark and Friesen (2009), Thoma (2016), and Avdeenko et al. (2019).

experimentation in a world in which both own ability and external circumstances co-determine outcomes (Hestermann and Le Yaouanq, 2021; Comin et al., 2022).[4] We refer to this prediction as the 'confidence–experimentation conjecture' (CEC). For testing the CEC, we choose a technology adoption context with an additional dynamic that renders experimentation more consequential. This dynamic additionally rewards experimentation in that sticking with incumbent technologies leads to a productivity penalty over time. As a result, reduced experimentation not only means foregoing productivity gains, but suffering expected losses. Such losses could disproportionately affect females if they are less likely to have positive and more likely to have negative confidence bias (Li and Zafar, 2023).

The field context in which we test the CEC is upland rice cultivation by smallholder farmers in West Africa.[5] Geographically, this is a climate change hot-spot: yields of existing rice varieties are expected to decline by more than 50% in the coming years, mainly as a result of drought events (Hultgren et al., 2025).[6] In this context, smallholders have to be willing to make changes in their production practices (including the variety they cultivate) to adapt to what are predicted to be rapidly shifting climatic and agroecological conditions and remain productive. Public breeding efforts have resulted in new drought-tolerant high-yielding ARICA rice varieties. The ability of farmers to harness these new varieties will be critical for the viability of their farms and for their livelihoods. This process of adaptation and innovation will require experimentation and learning from experimentation. Our paper focuses on the first of these requirements: on-farm experimentation for climate change adaptation. There, it investigates whether confidence is a significant predictor of demand for experimentation.

To identify our relevant study population, we conduct a regional producer census

[4]While lacking individual doctor-level observations, hospital-level adoption patterns of new medical procedures are at least consistent with this prediction (Comin et al., 2022).

[5]Upland rice production has little in common with large-scale irrigated paddy cultivation: fields are typically dry and well-draining and water is supplied irregularly through natural precipitation. As a result, exposure to climate-related shocks is high (Bernier et al., 2008). Rain-fed upland rice farming is a mainstay of West African agriculture, accounting for the largest share of rice-growing area (43%) in the region (Adjah et al., 2022).

[6]Agriculture counts among the first sectors to be seriously affected by global climate change. This statement is particularly relevant for African agriculture (Schlenker and Lobell, 2010), which is expected to be hit hardest by increases in weather extremes, such as prolonged drought (Giorgi et al., 2019). In West Africa, for example, drought duration is predicted to double from approximately two months on average in the past (1950–2014) to approximately four months in the period 2050–2100 (Ukkola et al., 2020).

in northern Côte d'Ivoire and southern Mali, followed by a baseline survey with the study population in 2024 before implementing the experimental survey with a final sample of 1,957 upland rice producers. We administer a context-appropriate battery of questions to calculate different metrics of confidence (Moore and Healy, 2008) and implement incentivized elicitations of their risk attitudes (Tanaka et al., 2010; Liu, 2013) and ambiguity aversion (Bryan, 2019; Abdellaoui et al., 2024) parameters during face-to-face interviews. Finally, we identify farmers' willingness to pay for an experimentation kit with drought-tolerant ARICA seed using a Becker-DeGroot-Marschak (BDM) mechanism.

We have three main findings. First, confidence bias constitutes an independent behavioral dimension of farmer characteristics: previously identified determinants of experimentation such as risk attitudes or ambiguity aversion cannot be relied upon to statistically construct an individual's absolute and relative confidence in performance. Second, confidence bias is positively and significantly associated with revealed demand for experimentation, providing support for the CEC. Splitting the sample into over- and underconfident producers reveals that the overall effect is solely driven by underconfident producers bidding significantly less for experimentation kits than unbiased producers, whose bids for kits do not significantly differ from overconfident producers. The effect size amounts to around 10 percent lower willingness to pay for experimentation, with the most affected being willing to pay 14 percent less. When kits are provided through the BDM elicitation, this leads to underconfident producers being substantially underserved; in our experiment, 10% fewer of these producers receive the experimentation kit than unbiased and overconfident producers.[7] Third, the evidence in support of the CEC – and of the role of underconfidence therein – is robust to choosing alternative outcome variables such as stated willingness to experiment.

Our findings contribute to the literature on the economic consequences of individual confidence bias: The CEC turns out to have empirical traction in a relevant field setting in which experimentation is a prerequisite for long-term maintenance of farm productivity. Traditionally, overconfidence is singled out for giving rise to distortions and economic costs (Malmendier and Taylor, 2015). What stands out in our findings is that underconfidence in explaining farmers' lower demand for experimentation. Underconfidence thus appears to be an important and understudied behavioral friction reducing experimentation levels.

[7]We calculate that if the kits were offered at cost (at about US$1.43 per kit), about 10% fewer underconfident producers (relative to overconfident and unbiased producers) would be willing to purchase the kit at that price.

The findings also contribute in particular to a literature on climate change adaptation in agriculture (Burke and Emerick, 2016) and beyond (Stern, 2008; Kahn, 2016). More generally, they also have bearing on technology adoption in other settings in which rapid change (e.g. deindustrialization or the adoption of artificial intelligence in the workplace) necessitates experimentation more broadly. Finally, the results point to novel pathways towards supporting experimentation by end-users. Such pathways will have to target the sources of underconfidence among potential experimenters, for example conformity to stereotypes (Bordalo et al., 2016). Documented success of interventions targeting self-beliefs in the form of self-efficacy training (McKelway, 2025) or cognitive behavioral theory (Blattman et al., 2017) raises the possibility that similar approaches could also be impactful for underconfident individuals that would benefit from experimentation.

2. Conceptual Framework and Hypothesis

After several decades of increasingly sophisticated research starting with Svenson (1981), it is generally accepted that a substantial part of the population holds biased beliefs about their own ability (Olsson, 2014; Dubra et al., 2015). This means that when individuals complete tasks of varying difficulty and are asked to predict their own performance, the error between their assessment and the true performance exhibits regular patterns. These patterns are that individuals tend to overestimate their score in absolute terms (estimation bias) and also tend to place themselves higher in the performance distribution in relative terms (placement bias). Some of these patterns can be explained away by measurement issues, in particular the "hard-easy effect" (Olsson, 2014) or by Bayesian learning (Benoît and Dubra, 2011). Still, an irreducible amount of confidence bias survives even highly stringent tests (Dubra et al., 2015).

Recent work has suggested a possible link between confidence bias and willingness to experiment, a key driver of technological change. Hestermann and Le Yaouanq (2021) show theoretically that for such decisions, errors in correctly estimating the influence of own ability and external factors can be consequential. In their model, which considers self-serving attribution bias as the source of misperceptions in learning from past returns, overestimation will on balance lead to a greater and underestimation to a lower willingness to experiment than for an unbiased individual. The reason is that an individual who overestimates own ability also overestimates his or her role when favorable returns materialize – and conversely for unfavorable returns. At the same time, estimates of the importance of external factors such as an environment (e.g., a workplace) or technology used are biased downwards relative to the current technology or environment. The same logic holds in reverse for an individual who underestimates own ability. As a result, underconfident individuals are predicted to underestimate the value of trying out new technologies and environments. Those overestimating their ability enter a self-correcting process since they gather more data by experimenting more and – in a stable environment – reduce estimation errors over time. Those underestimating their ability, on the other hand, forego the corrective learning associated with experimentation and instead risk being trapped in a low-returns situation that they misattribute to their own lack of ability rather than the low productivity of the chosen technology.

Comin et al. (2022) develop a theoretical model in which physicians' adoption decision regarding a new medical technology (here: implantable cardioverter defibrillators) obeys a benefit-cost calculus from the patient's point of view. The distortion in the adoption decision comes from Bayesian physicians holding possibly biased beliefs (priors) about their skill of implanting the new technology. Overconfident physicians overestimate the benefits for the patient of defibrillator implantation. This leads to temporary excess adoption before clinical outcome data can correct the confidence bias. In the absence of individual physician-level data, their empirical implementation is forced to revert to hospital-level data to build a plausible case.

Against the background of this 'Confidence-Experimentation Conjecture' (CEC), our conceptual framework is characterized by three dimensions. One is our focus on the full confidence bias distribution and not exclusively the phenomenon of overconfidence. This reflects our reading of Hestermann and Le Yaouanq (2021) that in welfare terms, underconfident individuals may well be the most relevant subpopulation in the context of technological change. The second dimension is the choice of context. Decisions about experimentation could be studied in many settings. We opt for technology experimentation by smallholder farmers, one of the most intensely studied settings in the literature on technological change. Specifically, we examine the decision by producers to trial new high-yielding rice varieties specifically developed by AfricaRice in collaboration with other national public breeding institutes to tolerate the increasingly frequent drought conditions in West Africa, a climate change hot-spot. In highly variable environments such as subsistence agriculture, inaccurate assessments of own ability can be persistent among producers (Huffman et al., 2022; Hoel et al., 2024), in particular if the learning process is characterized by misperceptions (Coutts et al., 2024), complicating the cognitive task of attribution (Bénabou and Tirole, 2002; Steen, 2004). The presence and persistence of such biases can then interfere with decision-making processes (Graeber, 2023; Coutts et al., 2024). One such decision is whether to experiment with a new, unfamiliar crop variety, a prerequisite step in technology adoption at the farm level.

Given the rich literature on farm-level technology adoption, we want to account for individual attitudes towards uncertainty at the point of choice by eliciting risk and loss attitudes, their probability weighting, and their ambiguity attitudes. Following Tanaka et al. (2010) and Liu (2013), a common approach is to approximate prospect valuation and probability weighting through functions that return three parameters (σ, λ, and α) as the target of the elicitation exercises using multiple price lists, with $\sigma < 1$ indicating risk aversion, $\lambda > 1$ indicating loss aversion, and $\alpha < 1$ indicating overweighting of small probabilities. The elicitation of ambiguity attitudes, on the other hand, implements different variations of the typical Ellsberg urn experiment (Ellsberg, 1961), such as Keller et al. (2007) and Bryan (2019). Since the smallholders in our setting will decide on whether to give up money in order to experiment, eliciting these four behavioral parameters is a natural starting point.

The third dimension is that we elicit individual-level data at a large-scale to test and quantify a possible link between confidence bias and individual experimentation. To our knowledge, ours is the first paper that is able to draw on such fine-grained data to examine this link. We administer a context-adjusted test battery to measure smallholder confidence in order to detect deviations between perceived and actual performance both in absolute terms (over- and underestimation) and in relative terms (over- and underplacement). The data on confidence bias is then linked–at the individual level–to non-hypothetical experimentation decisions elicited through a BDM mechanism that measures willingness to experiment as the willingness to pay for an experimental kit with novel seeds for small-scale plot trials.

With these three dimensions in place, we test the hypothesis that confidence bias is positively associated with willingness to experiment with climate-resilient rice seed. The main test is supported by extensive controls for possible confounds such as risk attitudes, past experimentation, and gender and secondary analyses.

3. Context, Sample Selection & Empirical Approach

A. Context

The geographical context of this study is the rice-growing region of northern Côte d'Ivoire, specifically the Savanes District, and southern Mali, in the Sikasso region. This location represents a climate change hot-spot characterized by a rapidly increasing risk of prolonged droughts (Ukkola et al., 2020), in which rice yields – absent adaptation – are expected to decline precipitously in the coming decades (Hultgren et al., 2025). Rice cultivation is characterized by smallholder agriculture, with an emphasis on subsistence: smallholders typically cultivate between 0.5 and 2 ha.

The study was implemented in collaboration with two local partners, AfricaRice and the Institut d'Economie Rurale in Mali. AfricaRice is an international CGIAR Research Center which has worked in partnership with the national agricultural research systems (NARS) of African nations through the Africa-wide Rice Breeding Task Force to develop more productive and resilient rice varieties suitable for cultivation in Africa. In both Mali and Côte d'Ivoire, regulations of the Economic Community of West African States allows varieties released in one country to be used in others in West Africa. AfricaRice is well known for its development of the New Rice for Africa (NERICA) varieties, created through interspecific hybridization to combine the high yield of Asian rice varieties and the local adaptability of African rice (Diagne, 2006). More recently, AfricaRice has worked to develop a new generation of resilient and high-yielding rice varieties called 'Advanced Rice Varieties for Africa,' or ARICA varieties. In our study, we utilize two drought-tolerant upland varieties from this latest generation with similar yields and characteristics: ARICA 14 and 15.

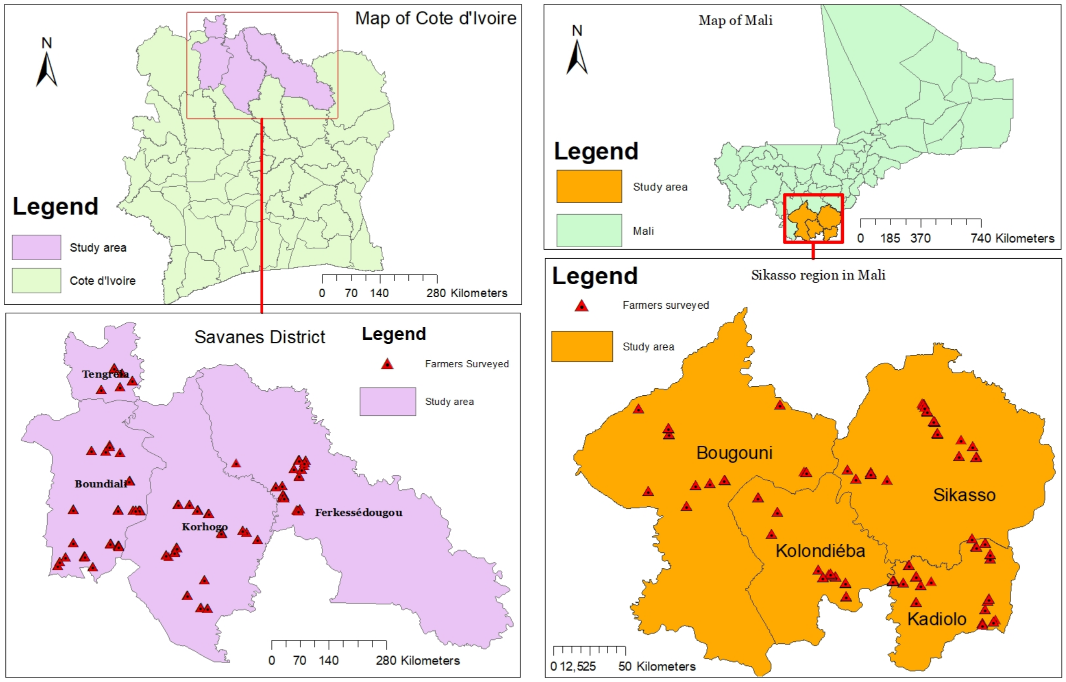
B. *Sample Selection*

The construction of our empirical sample employed a stratified, purposeful selection strategy. We began by identifying one hundred villages across two West African nations: fifty within Côte d'Ivoire's Savanes District and fifty within Mali's Sikasso region.[8] The primary criterion for inclusion at the village level was the confirmed prevalence of upland rice cultivation, which defines the population of interest for this inquiry. Figure 1 presents four maps: The map in the upper-left corner shows the location of the study area within Côte d'Ivoire, the map in the upper right corner that for Mali. The map in the lower-left corner provides study location information as red triangles within the study region for Côte d'Ivoire. The map in the lower-right corner has the same information for Mali.

The first field campaign had enumerator teams enter the study villages and conduct a quick census of all producers in the village, with the goal of identifying individuals who produce upland rice; planned to cultivate rice in the coming season; and who decide what variety of rice to grow on their plots. This resulted in a census of 2,019

[8]Target areas were the *départements* of Tengrela, Boundiali, Korhogo, and Ferkessédougou in Côte d'Ivoire and the *cercles* of Bougouni, Sikasso, Kadiolo, and Kolondiéba.

Figure 1. : Map of the study villages in Côte d'Ivoire & Mali.



Note: Left panels–information for Côte d'Ivoire. Right panels–information for Mali.

Study locations (N = 100) in both countries are marked with red triangles.

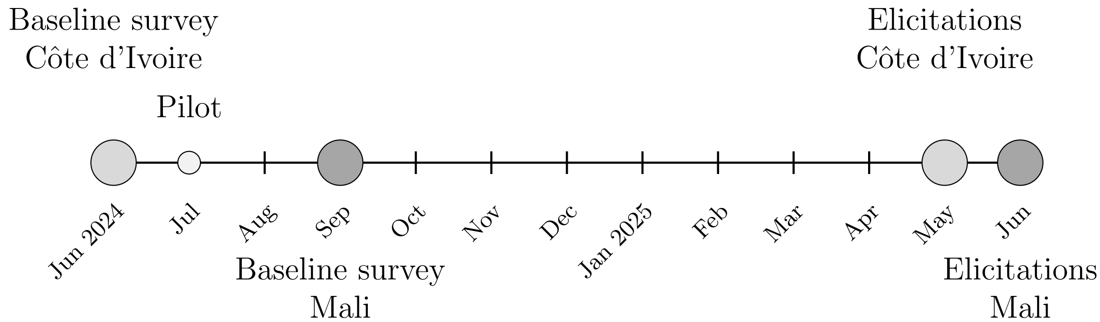
rice producers in Mali and 2,310 in Côte d'Ivoire. Each village typically had about 40-50 upland rice producers who were included in the census data collection.

Once the census was complete, enumerators selected 20 producers from each village for the longer, baseline survey which contained questions on producer characteristics, household structure, and overall agricultural activity (for a total of about 2,000 producers across both countries). The selection was conducted randomly, except in cases with gender imbalances in the villages. In these cases, the underrepresented gender was over-sampled.

The first campaign was implemented in June 2024 in Côte d'Ivoire and September 2024 in Mali (see timeline in Figure 2). A pilot of the elicitation survey took place in July 2024 in two villages in Côte d'Ivoire, Tiekpe and Kipetchirguevogo.

We conducted the main elicitation campaign in the remaining 98 villages in May 2025 in Côte d'Ivoire and June 2025 in Mali. Of the resulting 1,961 producers, we

Figure 2. : Timeline of data collection in Côte d'Ivoire & Mali.



Note: The timeline starts in June 2024 with baseline survey in Côte d'Ivoire, followed by the pilot in two villages in the same country in July. The baseline survey in Mali is conducted in September 2024. The elicitations took place in Côte d'Ivoire in May 2025 and in Mali in June 2025.

excluded four based on concerns they could be duplicate records. This leaves a final sample of 1,957, which we calculated to be just over the number of observations required to detect a conventionally small effect size (Cohen's $f^2 = 0.01$) using up to sixteen explanatory variables.

C. Measurement of confidence-related variables

We employ conventional measures of confidence bias by administering a seven-item battery of questions (see appendix A.4. for the full questionnaire) with binary answer possibilities, each item being followed by an elicitation of how confident the participant is that the answer is correct (Moore and Healy, 2008). Our favored metric of confidence bias is over- and underestimation, respectively, as it better captures the producer's self-assessment of their knowledge (in absolute terms). In light of the literature (Murad et al., 2016; Lebreton et al., 2018; Bryan, 2019), we chose not to incentivize our confidence elicitation, in particular to avoid an interference between a possible endowment effect and the BDM elicitation of WTP.

The elicitation questions cover knowledge aspects related to the agricultural context of the rice farmers, from meteorology to best farming practices and extension services. The battery was pre-tested during the pilot to check for difficulty and in order to avoid well-known biases in confidence tests. Following these questions, the battery concludes with two key questions to the participant. The first elicits their belief about absolute performance, that is, the number of questions they answered correctly, between 0 and 7. The second elicits their belief about relative performance, that is, the placement of their performance below, above, or at the median among the farmers in their village.

Two main metrics result from this section in the survey, our preferred metric of confidence bias (equivalent to under- and over-estimation) and a metric of under- and overplacement. To construct the confidence bias, we compute, for each participant, the true number of correct answers (A_i^t) and the expected number of correct answers (A_i^e). On this basis, we assign to each participant i a level of confidence bias $B_i = A_i^t - A_i^e$, with a positive score ($B_i > 0$) indicating overconfidence (overestimation) and vice versa. Other outcomes defined on this basis and used in subsequent analysis are the level of underconfidence, defined as $max\{0, A_i^t - A_i^e\}$, and the level of overconfidence, defined as $max\{0, A_i^e - A_i^t\}$.[9]

To construct the placement metric, we compute, for each participant, their true performance percentile at the village level and compare this with their predicted placement. We assign to each participant a dummy of underplacement, which is 1 if their true placement is better than their prediction and 0 otherwise. Analogously, we assign to each participant a dummy of overplacement, which takes the value of 1 if their true placement is worse than their prediction and 0 otherwise.

In addition to the two main measured metrics, we also use self-reported metrics of self-confidence. Each farmer is asked to rate their rice-growing skills in comparison to their village peers (see Barsbai et al. (2022) for a similar approach) and to rate their rice varieties in comparison to those grown in the village and the region.

D. *Measurement of prospect theory parameters*

We rely on a mature literature on prospect theory parameter elicitation in the field. Much of this builds on Tanaka et al. (2010), who use a multiple price list method based on Cumulative Prospect Theory to elicit risk aversion (utility function curvature), loss aversion, and probability weighting from individuals in Vietnam. Like many other papers (see also Liu (2013)), we follow this approach to measure – for each farmer – three prospect theory parameters: σ (the concavity of the utility function, a measure of risk aversion), λ (loss aversion), and α (probability overweighting). To improve external validity and improve subjects' understanding (Cerroni, 2020), we contextualize the three sets of price lists to the specific setting of choosing a rice variety (see Appendix A.4).

The prospect theory parameter elicitation took place after the battery of confidence

[9]See section 4 for Robustness Checks with respect to the choice of bandwidths around zero bias.

questions. Enumerators used a set of diagrams on paper to illustrate the choices (see Appendix A.3 for an example). Before beginning, the producers were told that their choices would be consequential in that one of the scenarios would randomly be drawn and they would be paid out a percentage of the amount shown based upon their answers. The compensation for the risk preference elicitation occurred at the end of the experiment so as not to bias the rest of the survey and the other experimental components.

E. Measurement of ambiguity aversion

Elicitation of ambiguity aversion in the field largely relies on variations of Ellsberg (1961)'s classic two-color urn experiment (Barham et al., 2014; Bryan, 2019). Individuals in our sample are asked how much they are willing to pay (elicited using the BDM method) to participate in two scenarios. In one of them, they have the option to take a ball out of an urn with a known quantity of black and white balls (50-50). In the other, they have the option to take a ball out of an urn with an unknown proportion of black and white balls. The objective is to win a monetary reward, which requires that the color of the ball taken out of the urn match the individual's choice of predicted color.

Ambiguity aversion is measured as the difference in the WTP to participate in the 50-50 scenario and the WTP to participate in the scenario with an unknown proportion of black and white balls. This is because ambiguity-averse individuals would be willing to pay more to play the urn with known odds compared to the urn with unknown odds – and vice versa for ambiguity-loving individuals. WTP was bounded from below at zero and from above at 1000 FCFA. Appendix A.4 presents the precise framing of the ambiguity aversion elicitation.

The WTP of the respondents was used to determine whether they would have the chance to play either of the two choice scenarios (selected at random). Successful respondents were then allowed to play and potentially win 1000 FCFA at the end of the survey, after the other elicitations had been completed.

F. Measurement of producer demand for experimentation with drought-tolerant rice seed

Like Berry et al. (2020), Burchardi et al. (2021) and Dizon-Ross and Jayachandran (2023), we employ a BDM mechanism to elicit producer WTP for an ARICA experimentation kit. Each kit contained 25g of ARICA seed, a metal stake to mark the experimentation plot, a plastic container to measure out 25g of the producer's own rice seed, and a 2m-long string to measure out 2m x 2m experimentation plots to compare their own variety's performance relative to the ARICA variety provided.[10]

The survey protocol instructed enumerators to describe the ARICA variety contained in the seed bag as an upland variety developed by AfricaRice with the favorable production properties (high yield, good disease resistance) as well as strong tolerance to drought conditions during cultivation. The enumerator informed the producer before they bid that if they received the seed that the recommended procedure was to cultivate the ARICA variety during the current growing season in a small experimental plot (2m by 2m) alongside an identical small plot of their own rice variety.

Potential WTP values ranged from 0 to a maximum of 1600 FCFA. To cover costs, kits would have to be exchanged for at least FCFA 800 per unit.[11] The BDM elicitation for the experimentation kit was always preceded by a trial BDM elicitation for a bag of fertilizer in order to improve participants' comprehension of the procedure, familiarity with the steps, and confidence in the truthfulness of the instructions given.

At the conclusion of the BDM elicitation, based upon the dice roll, the producer either received the seed (for the price associated with the dice roll), or did not receive the seed (and did not pay).

In addition to the revealed preference BDM elicitation of producer demand for the ARICA experimentation kit, we also asked each producer in the sample whether they would be willing to conduct a trial with drought-tolerant rice seed with characteristics similar to the ARICA varieties on 10%, 50% and 100% of their rice cultivation area.

G. Empirical Approach

Our main set of regressions test whether variations in confidence make a statistically significant contribution to explaining variations in the individual willingness to experiment (WTE), controlling for relevant co-variates.

Different measures are used to implement WTE as the dependent variable. Our primary implementation is producer i's BDM-elicited willingness-to-pay for ARICA seed (in CFA francs). Our secondary implementation is producer i's stated binary willingness to conduct a trial with drought-tolerant rice seed with characteristics

[10] Appendix A.3 provides an image of the experimentation kit, A.4 the enumerator script.

[11] The seed sample package cost an estimated US$0.60, the measuring cup US$0.35, the measuring string US$0.18, the metal stake US$0.35, for a total of approximately US$1.43 per kit or FCFA 800.

similar to the ARICA varieties used on successively increasing shares of their available plot, rising from 10% to 50% and to 100%.

$$WTE_{ive} = \beta_1 + \beta_2 \times \text{Confidence}_{\text{i}} + \mathbf{X}_{\text{i}}' \times \alpha + \mu_v + \lambda_e + \varepsilon \tag{1}$$

In our main estimation equation (1), the independent variables are β_1, a constant, a vector of producer confidence measures, and a vector of co-variates X_i identified in our conceptual framework as potential drivers of WTE (including placement and the behavioral variables we elicited – σ, λ, α, and ambiguity aversion). Depending on the specification, we add a set of village controls μ_v and a set of enumerator controls λ_e. ϵ is the error term. (Robust) standard errors are clustered at the village level.

4. Results

A. *Descriptive Statistics*

Table 1 reports summary statistics for the pooled sample of producers across both countries.[12]

The farmers in our sample are typically male (68%), in the mid-thirties to late fifties (mean: 47 years), and cultivate a hectare of land. They report a median income of $50,000$ FCFA (around US$85) per month.

Starting with measures of confidence, specifically overestimation, our test battery returns a mean confidence level of 0.08 (median: 0).This means that on average, the farmers in our sample are slightly overconfident. Figure 3 presents, in the left panel, the distribution of the confidence bias (as measured by under- and overestimation) in our sample. The sample distribution aligns with evidence on the Dunning-Kruger effect in Western countries (Jansen et al., 2021): Splitting the sample at the midpoint of the scale, our test battery would classify 34.8% of the sample as underconfident and 42.3% as overconfident. The right panel of Figure 3 presents the results when the placement metric is used instead of confidence bias in estimation of own performance. Here, we find that the sample contains 24.4% of farmers who underplace and 40% who overplace themselves relative to their village peers, with the median farmer placing themselves in the distribution correctly.

[12]Table A1 in the appendix provides a breakdown of the main variables used in the analysis by country.

Figure 3. : Histogram of confidence bias and placement.

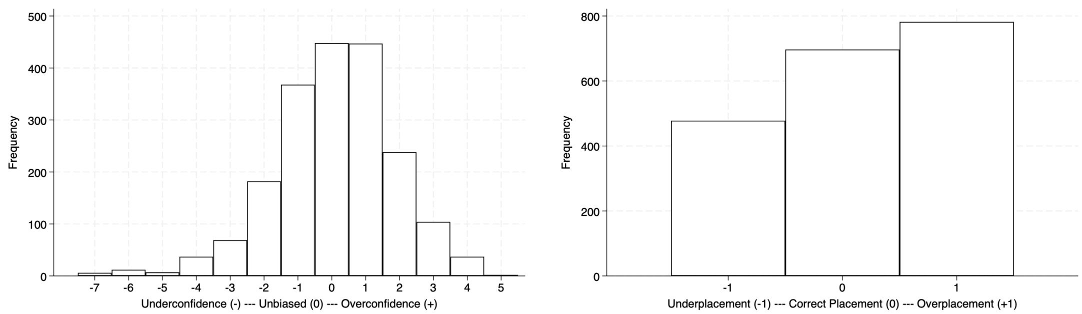


Table 1: Summary Statistics for Behavioral Variables & Producer Characteristics

Variable	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**N**
Age	47	47	11.23	15	89	1957
Female	0.319	0	0.466	0	1	1957
Rice area cultivated (ha)	1.79	1	1.804	0.13	30	1957
Personal income, past month (1000s FCFA)	151	50	370.80	0	9500	1957
Confidence bias	0.08	0	1.78	-7	5	1957
Placement	0.164	0	0.130	-1	1	1957
σ	0.696	0.7	0.471	0	1.5	1957
λ	2.731	1.58	3.04	0.12	11.79	1957
α	0.724	0.7	0.235	0.05	1.45	1957
Ambiguity aversion (FCFA)	48.952	0	193.491	-900	950	1957
WTP (FCFA)	907	1000	381	0	1600	1957

The picture that emerges from Table 1 and Figure 3 is – on average – one of reasonable accurate self-perception of own performance among the rice farmers about to be offered an experimentation opportunity. At the same time, there is sufficient mass of farmers in the tails of the distribution, both for confidence bias and for placement, for variation in confidence to explain variations in the subsequent bidding for experimentation kits.

Table 1 reports on the four behavioral variables that characterize our sample.[13] The single-parameter characterization of risk aversion through σ (the curvature of the utility function) returns a value of 0.696 with a median of 0.7. Most farmers therefore exhibit choices that are consistent with moderate risk aversion. The value for the present sample aligns closely with the values (between 0.59 and 0.63) measured by Tanaka et al. (2010) for Vietnamese rice farmers, but higher–for instance–than the sample mean of 0.48 by Liu (2013) for Chinese cotton farmers. For loss aversion, λ, the elicitation returns a mean of 2.73. The mean aligns closely with the mean value for Vietnam of 2.63 reported by Tanaka et al. (2010) as well as a mean of 2.25 estimated by Tversky and Kahneman (1992). The Chinese cotton farmers are characterized by a mean value for λ of 3.47. While greater than the most comprehensive recent meta-analytical estimates with a mean of 1.97, the difference vanishes once the farmer subject pool is taken into account, which raises estimates by around 0.5 (Brown et al., 2024).[14] Most producers (62% of the sample) are characterized by $\lambda > 1$, indicating that they are loss averse. Only five producers exhibit preferences consistent with expected utility (where λ=1). For the shape of the probability weighting function, our sample returns a mean of α at 0.724. The Vietnamese rice farmers studied by Tanaka et al. (2010) return a mean of 0.74, the Chinese cotton farmer studied by Liu (2013) a mean of 0.69. Like these authors, we find that most producers in our sample do not exhibit preferences consistent with expected utility, and that the majority of the sample exhibit inverted-S shaped probability weighting, meaning that they overweigh small probabilities. Ambiguity aversion, on the other hand, characterizes a minority of our sample. About 54% of producers are ambiguity-neutral, 31% are ambiguity-averse, and 15% are ambiguity-loving. The mean value of ambiguity aversion in the sample of about 50 FCFA indicates a small average degree of ambiguity aversion in the dataset. This makes our sample more ambiguity-tolerant than, for example, the comparable Kenyan sample in Bryan (2019), in which 59% are ambiguity-averse.[15]

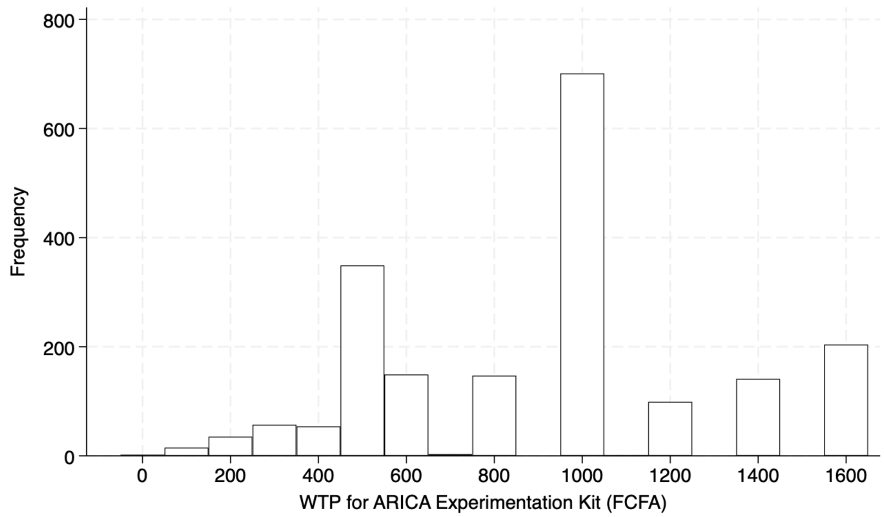
The final summary statistic reported in Table 1 is the WTP for the ARICA experimentation kit among the farmers, determined in the BDM elicitation at the end of the survey. Mean WTP in the sample was 907 FCFA with a median of 1000 FCFA. To put this in perspective, the median implies that more than half of the sample would acquire the kit if sold at cost (800 FCFA). Figure 4 illustrates the variation in

[13] Appendix A.5 features histograms for the empirical distributions of the elicited values.

[14] The estimate is based on a dataset of 607 estimates reported in 150 papers from economics, psychology, neuroscience, and related fields.

[15] The paper does not single out the share of ambiguity-loving participants in Kenya. The Malawi sample cannot be readily compared because of differences in the urn loadings.

Figure 4. : Histogram of WTP for ARICA experimentation kit.



WTP in the sample: There is positive support for each of the twelve discrete price points offered in the interval $[0; 1600]$. Focal points of WTP are $1,000$ FCFA, which accounts for over a third of the sample, and 500 FCFA, which accounts for around a fifth. Around 10 percent of the sample express a willingness to pay of at least $1,600$ FCFA for the kit. We cannot exclude that there are some individual farmers whose WTP exceeds the upper bound, but it is also clear that roughly 90 percent of the mass of the WTP distribution lies within the price interval.

B. Correlation of Behavioral Variables

The four risk attitudes and the two confidence attitudes (self-estimation and placement) elicited among our farmer sample are conceptually independent dimensions with which to characterize a decision-maker facing an experimentation decision. In practice, this conceptual independence is threatened by two main issues. One is methodological: The nature of the elicitation mechanism can give rise to undesirable interactions between different attitudes. For example, while providing a more accurate picture of capabilities, incentivized confidence tasks can also interact with risk attitudes when subjects are induced to pool and hedge across questions (Lebreton et al., 2018). The other is empirical: The researcher cannot exclude ex ante that behavioral dimensions strongly correlate in the population. For example, risk-loving attitudes and positive confidence bias could conceivably co-occur on a systematic basis, preventing a clear attribution of variations in WTE to either dimension.

Table 2: Correlation Matrix of Behavioral Variables

Variable	Confidence	Placement	σ	λ	α	Ambig. Av.
Confidence	1.00					
Placement	0.48	1.00				
σ	-0.02	0.02	1.00			
λ	-0.01	0.07	-0.35	1.00		
α	-0.04	-0.01	-0.02	-0.09	1.00	
Ambiguity aversion	0.02	0.01	-0.01	0.03	-0.04	1.00

The results in Table 2 show that the second concern is unfounded. The correlation matrix for the six behavioral dimensions reports correlations that are close to zero, with two exceptions. One is a clear positive correlation (0.48) between confidence bias and placement: Those with exaggerated beliefs in their own performance also tend to have optimistic beliefs regarding where their performance lies relative to that of their peers. The other exception is a clear negative correlation (-0.35) between the risk aversion variable σ and the loss aversion variable λ. With greater values of σ signifying smaller loss aversion and greater values of λ signifying greater loss aversion, the negative correlation indicates that in our sample, individuals exhibiting higher levels of risk aversion also tend to exhibit higher levels of loss aversion. Importantly, none of the variables measuring risk attitudes correlate with confidence bias or placement. We interpret this as evidence that biased beliefs in one's abilities constitute a distinct behavioral dimension of the producers in our sample that cannot be inferred on the basis of commonly elicited behavioral variables.

C. Confidence Bias & Demand for Experimentation with ARICA seed

Table 3 reports the first set of main findings. The underlying specifications follow equation (1), with BDM-elicited WTP as the dependent variable.

Model 1 features confidence bias as the only explanatory variable, with an estimated coefficient of 13.41. On average, therefore, a positive one-score change in confidence bias is associated with an increase in WTP of around 13 FCFA. This coefficient estimate and its high statistical significance turn out to be highly robust to richer specifications. Model 2 adds placement as an explanatory variable, leaving WTP slightly more sensitive to changes in confidence bias by raising the coefficient to the equivalent of 16 FCFA per score, but returning no significant result for placement. Model 3 examines the WTP data exclusively through the lens of prospect theory parameters (σ, λ and α) and ambiguity aversion, excluding the dimension of confidence bias. Like Liu (2013) on adoption, we find that risk aversion has a significant impact on WTP for experimentation, but in the opposite direction: More risk-averse farmers are more likely to exhibit a higher WTP. This can be explained both by the nature of the technology offered (providing greater drought-tolerance) and by the fact that our sample is asked to consider not an adoption, but an experimentation decision. Experimentation can be risk-reducing if it generates low-stakes farmer experience with a new technology prior to making the adoption decision. The other behavioral variables do not return statistically significant coefficient estimates. This evidence from experimentation decisions contrasts with evidence from adoption decisions in a farming context. There, Barham et al. (2014) find that ambiguity aversion furthers adoption of what could be regarded as an uncertainty-reducing technology.

Model 4 combines the six behavioral variables in a single specification. The results reaffirm the main message of Models 1 through 3: Confidence bias and risk aversion are both positively and significantly associated with WTP for experimentation. The other variables return stable, but statistically insignificant estimates. These results diverge from empirical evidence on labor market entry decisions that share some parallels with experimentation. (Gutierrez et al., 2020) find that overconfidence and ambiguity attitudes jointly, but separately impact on market entry decision. In our sample, only confidence bias relates to experimentation in a significant way.

Model 5 augments Model 4 with both demographic as well as self-reported performance variables. Neither gender nor country significantly affect WTP. A possible gender effect in the demand for experimentation must therefore be channeled through confidence bias (Deaves et al., 2009). WTP is significantly and positively related to a farmer's self-assessment that they possess above-average farming skills and cultivate a variety among the best in the region, as well as those who self-report higher yields. There is little impact of including these variables on the coefficient estimates of confidence bias and risk aversion. This highlights that broader measures of confidence in own ability, own technology, and own past performance additionally explain WTP.

Model 6 addresses a possible concern stemming from the confidence bias variable being constructed as a difference between two outputs of the test battery, namely a belief in own performance and actual performance. As a result, only one of the two components might conceivably drive the results attributed to confidence bias. We therefore decompose confidence bias into its two components in order to investigate the possibility that the confidence bias effect is – in effect – a performance belief or a skill (performance) effect. The analysis in Model 6 does not support this idea: Individually, neither component is significantly associated with WTP, while their difference, confidence bias, is.

Table 3: Confidence, Placement, and Demand for Experimentation

Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
Confidence	13.41**	15.62***		15.54***	14.58**	
	(5.249)	(5.659)		(5.700)	(5.646)	
Placement		-9.701		-9.489	-11.12	20.813
		(14.91)		(14.79)	(14.55)	(19.585)
σ			-59.624**	-58.53**	-52.73*	-54.160*
			(29.015)	(28.92)	(29.05)	(29.338)
λ			-2.387	-2.400	-2.405	-2.760
			(3.243)	(3.241)	(3.276)	(3.302)
α			25.371	29.11	32.32	29.296
			(40.194)	(40.38)	(40.03)	(39.817)
Ambiguity aversion			0.196	-0.0552	0.0410	0.030
			(4.648)	(4.635)	(4.672)	(4.691)
Below-average skills					-0.916	-1.872
					(41.10)	(42.095)
Above-average skills					39.15***	38.315***
					(13.74)	(13.597)
Average yield					0.466***	0.419***
					(0.104)	(0.101)
Below-average var.					-25.24	-29.159
					(40.30)	(41.131)
Among-best var.					51.49*	48.802*
					(29.33)	(29.174)
Mali					105.2	34.972
					(74.63)	(78.610)
Female					5.643	6.089
					(37.04)	(37.194)
Female × Mali					-57.98	-58.540
					(46.93)	(47.056)
Estimated score						29.939
						(21.048)
Actual score						16.362
						(11.298)
Constant	804.1***	804.7***	883.077***	846.3***	787.7***	561.694***
	(12.59)	(12.82)	(76.463)	(79.96)	(90.00)	(169.329)
Enumerator and village controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,957	1,957	1,957	1,957	1,957	1,957
R-squared	0.219	0.219	0.219	0.222	0.229	0.229

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Mean WTP: 907 FCFA; Median WTP: 1000 FCFA. Ambiguity aversion measured in 100s FCFA. Average yield is self-reported and measured in tons.

The results reported in Table 3 provide an estimate of the impact of confidence bias under the assumption that positive and negative biases have symmetric effects. It is plausible, however, that overconfidence and underconfidence affect the willingness to experiment differently. In fact, theory suggests a level of asymmetry in the dynamics of over- and underconfident agents (Hestermann and Le Yaouanq, 2021) in that the underconfident stay trapped in a low-productivity situation while the overconfident reach higher productivity while undergoing bias correction.

Table 4 reports the results of a WTP analysis when allowing for asymmetric effects of positive and negative bias. This analysis splits the sample into those with negative and positive bias in estimation and placement, with zero bias as the baseline. Model 1, which relies on positive and negative confidence bias as explanatory variables only, shows that the there is a strong and highly significant negative effect of underconfidence on willingness to experiment. Increasing underconfidence by one score decreases WTP by an estimated average of 24 FCFA. Overconfidence, on the other hand, has a substantially negligible and statistically insignificant effect on WTP. This is evidence that the average effect in Table 3 obscures an important asymmetry in that it appears to be solely driven by those farmers who are underconfident. Looking ahead to the following models, the coefficient of underconfidence remains stable across specifications both in terms of sign, magnitude and significance.

Model 2 closely mirrors Model 5 in Table 3 both in terms of included variables and findings: Producers who stated that they consider their rice-cultivation skills to be better than average, and their current variety to be among the best, were willing to pay significantly more for the experimentation kit. Those who stated that their average yield was higher were also willing to pay more.

Model 3 allows for measurement error by reclassifying individuals as unbiased if the difference between actual performance and estimated performance is within one score up or down. To be classified as underconfident therefore requires a bias of -2 and vice versa for overconfident. Including the measurement error does not qualitatively alter the findings vis-à-vis Models 1 and 2. If anything, the main effect of underconfidence becomes slightly more pronounced.

Figure 5 unpacks the regression results of Model 3 further by plotting the estimated impact on the median WTP of 1000 FCFA of each individual level of under- and overconfidence as well as each coefficient's 95% confidence interval.[16] The pattern suggests any non-negative confidence bias has a negligible impact on WTP. For negative scores of -2 to -4, the impact is consistently negative, but not appreciably

[16]The associated regression is included as Table A2 in the appendix.

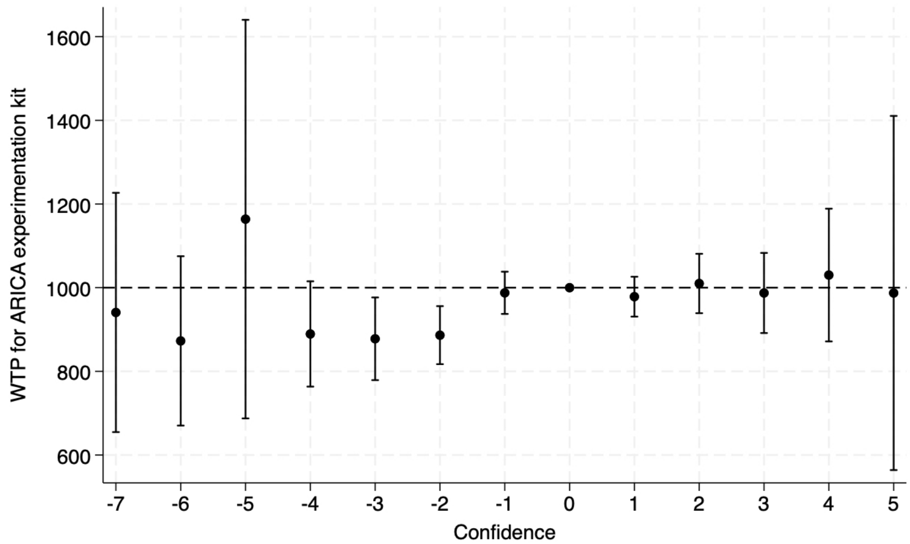
Table 4: Underconfidence and WTP for Experimentation

Explanatory variable	**(1)**	**(2)**	**(3)**	**(4)**
Underconfidence	-24.03***	-23.58***	-27.85**	-96.42***
	(8.702)	(8.638)	(11.19)	(24.96)
Overconfidence	0.351	0.656	8.652	17.38
	(10.32)	(11.75)	(16.41)	(27.70)
Underplacement		20.55	15.89	24.45
		(21.76)	(21.54)	(22.34)
Overplacement		4.847	6.203	-2.759
		(28.50)	(27.23)	(27.20)
σ		-50.49*	-50.99*	-47.45
		(29.09)	(29.12)	(28.90)
λ		-2.471	-2.532	-2.017
		(3.301)	(3.281)	(3.280)
α		34.02	33.46	34.93
		(39.89)	(40.27)	(40.26)
Ambig. av.		0.00223	0.119	-0.283
		(4.660)	(4.685)	(4.651)
Below-average skills		0.860	-0.349	3.371
		(41.16)	(41.48)	(40.73)
Above-average skills		39.21***	40.00***	39.21***
		(13.70)	(13.69)	(13.70)
Average yield		0.500***	0.489***	0.500***
		(0.104)	(0.106)	(0.104)
Below-average var.		-24.23	-22.76	-21.41
		(40.43)	(40.83)	(40.45)
Among-best var.		53.36*	53.02*	50.14*
		(29.51)	(29.27)	(29.40)
Mali		98.60	100.8	108.5
		(75.40)	(76.16)	(78.00)
Female		3.403	3.553	3.403
		(37.15)	(37.20)	(36.63)
Female × Mali		-54.53	-55.41	-51.71
		(47.17)	(47.43)	(46.49)
Constant	800.3***	785.4***	794.7***	785.4***
	(93.34)	(93.61)	(92.62)	(93.61)
Enumerator and village controls	Yes	Yes	Yes	Yes
Number of observations	1,957	1,957	1,957	1,957
R-squared	0.245	0.230	0.230	0.233

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ambiguity aversion measured in 100s FCFA. Average yield is self-reported and measured in tons.

worse for the more underconfident. Rather, WTP shifts down by roughly 100 FCFA for those clearly classified as negatively biased. For scores at the upper and lower end of confidence bias, there are too few observations to determine coefficients with sufficient precision.

Figure 5. : WTP for experimentation by confidence level



Notes: Willingness to pay for the experimentation kit, at each score of empirically observed confidence bias, anchored at median WTP (1000 FCFA). Point estimates are derived from an OLS regression with each level of confidence bias score as a dummy (baseline: zero bias). Error bars are 95% confidence intervals.

A specification that captures this pattern is Model 4 in Table 4. Like Model 3, it allows for measurement error around zero bias. Over- and underconfidence are dummy variables applied to bias scores of |2| or greater. This model estimates the downwards shift in WTP for experimentation associated with underconfidence as 96 FCFA. In other words, a producer who exhibits a confidence bias beyond plausible measurement error is willing to pay 10 percent less for the experimentation opportunity compared to an unbiased or positively biased producer. This difference would appear modest at first, but if experimentation is provided at cost, this has significant implications for the degree to which the underconfident avail themselves of experimentation opportunities.

D. Underconfidence and stated willingness to experiment

One concern with the results presented in the previous section is that the dependent variable, BDM-elicited WTP, may be susceptible to interference by confidence bias. The idea is that despite the training round with the BDM mechanism, in which a bag of fertilizer is used, producers with negative confidence bias fail to bid up to their true WTP because underconfident individuals are more likely to be hesitant to engage with the unfamiliar procedure. This would render our main result an artifact of the measurement method.

To address this concern, we investigate whether changing the dependent variable from the BDM-elicited WTP to a more conventional stated willingness to experiment returns results that are in line with the main result above. Data for stated willingness to experiment comes from survey questions to the producers. Farmers were asked sequentially whether or not they were willing to set aside 10%, 50%, and 100% of their plot for experimentation with a drought-tolerant rice variety with yields similar to ARICA 14 and 15. The set-aside of 10% is closest to the nature of the experimentation opportunity provided by the kit, which asks for a total of 8m^2 to be dedicated to experimentation with the new seed (including the comparison plot).[17] The set-aside of 100% is closest to a full adoption decision.

Table 5 reports the results of this analysis. Model 1 presents the results of an ordered logit regression across the three possible scales of experimentation. We code producers as 0 if they were not willing to set aside any percentage of their plot for experimentation, as 1 if they were willing to set aside only 10% of their plot, as 2 if they were willing to set aside 10% and 50% of their plot, and 3 if they were willing to set aside 10%, 50% and 100% to the new variety. In this specification, the estimated coefficient for underconfidence is economically negligible and statistically insignificant. Underplacement is found to be negative and significant, and overconfidence is positive and significant, consistent with the predictions of the CEC. In the ordered logit, we also find that less risk averse producers are more likely to state they are willing to set aside more of their plot for experimentation, while more loss averse producers are less likely to state they are willing to experiment. Female producers and producers from Mali are more likely to state that they are willing to experiment with the new seed, as well as producers who consider their rice farming skills to be above average, though those who consider their current variety to be among the best are less likely to be willing to experiment.

[17] For the median farmer with a cultivated area of 1ha, the trial requires less than 0.1% of land available.

Table 5: Underconfidence and Stated Willingness to Experiment

Explanatory variable	**(1)** **WTE Ordered**	**(2)** **WTE 10%**	**(3)** **WTE 50%**	**(4)** **WTE 100%**
Underconfidence	0.022	-0.218*	-0.026	0.007
	(0.050)	(0.124)	(0.092)	(0.050)
Overconfidence	0.255***	0.031	0.209	0.231***
	(0.072)	(0.130)	(0.133)	(0.070)
Underplacement	-0.338**	-1.224**	-0.144	-0.351**
	(0.139)	(0.504)	(0.258)	(0.139)
Overplacement	-0.102	-1.427***	-0.193	-0.099
	(0.135)	(0.452)	(0.246)	(0.134)
σ	0.248**	0.589	1.022***	0.177
	(0.119)	(0.410)	(0.250)	(0.121)
λ	-0.034*	-0.083**	-0.085***	-0.020
	(0.019)	(0.041)	(0.030)	(0.018)
α	-0.245	-1.031*	-1.599***	-0.048
	(0.236)	(0.604)	(0.417)	(0.232)
Ambig. Aversion	-0.032	0.086*	-0.032	-0.031
	(0.028)	(0.051)	(0.054)	(0.029)
Below-average skills	0.590*	-0.028	-0.066	0.673**
	(0.302)	(0.674)	(0.374)	(0.278)
Above-average skills	0.206**	-0.075	0.587***	0.137
	(0.085)	(0.215)	(0.190)	(0.086)
Below-average var.	0.439	-0.994*	0.365	0.455*
	(0.288)	(0.570)	(0.411)	(0.272)
Among-best var.	-1.309***	0.743**	0.645***	0.691***
	(0.348)	(0.364)	(0.173)	(0.172)
Average yield	0.007	-0.001	0.497**	0.003
	(0.015)	(0.002)	(0.226)	(0.002)
Mali	1.348***	-0.351	2.629***	1.221***
	(0.139)	(0.396)	(0.445)	(0.137)
Female	0.346**	-0.069	0.218	0.338**
	(0.162)	(0.487)	(0.236)	(0.155)
Female × Mali	0.187	0.367	-0.411	0.170
	(0.253)	(0.659)	(0.631)	(0.248)
Constant		0.056	6.141***	1.841***
		(0.827)	(0.633)	(0.250)
Enumerator and village controls	No	No	No	No
Number of observations	1,930	1,957	1,957	1,957

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ambiguity aversion measured in 100s FCFA. Average yield is self-reported and measured in tons. Models 2–4 are logit regressions for stated willingness to set aside 10%, 50%, or 100% of the plot. Model 1 is an ordered logit regression.

Model 1 provides a stepwise estimation that tacitly assumes convexity in choosing experimentation levels[18] and has at least two scales of experimentation (50% and 100%) that are difficult to distinguish from adoption. Model 2, by contrast, runs a logit regression on the single question of whether the producer is willing to set aside 10% of his plot for experimentation. Here, the pattern looks more comparable to that in Table 4. Underconfident farmers are less likely to volunteer their plot for even small-scale experimentation. Incidentally, the same is true for those underplacing themselves. Loss-aversion retains its negative sign and now becomes significant, as does whether producers consider their current variety to be below average. We also recover the positive effect of considering their current variety to be among the best as supportive of experimentation while considering the current variety to be below average is associated with a lower likelihood of being willing to set aside 10% of their plot for experimentation. Those who state that they consider their current variety to be among the best tend to be more likely to state they are willing to set aside 10% of their plot.

The empirical picture changes when farmers are asked to consider greater shares of their plot for experimentation. In Model 3 (WTE 50%), none of the under- or overconfidence variables are significant, although risk aversion (σ) is found to be positive and significant; loss aversion (λ) is found to be negative and significant; and producers from Mali, those who consider their current variety among the best, and those who think their rice farming skills are above average all tended to be more likely to state that they were willing to set aside 50% of their plot for experimentation. In Model 4 (WTE 100%), we find a similar pattern to the results of the ordered logit, where overconfident producers were more willing to set aside their entire plot for experimentation with a new variety, and producers who underplaced themselves were significantly less likely to to do so. In addition, we find several other significant results, including for producers from Mali and female producers, who were both more willing to set aside their entire plot.

E. Correlates of Underconfidence

Negatively biased beliefs about own ability could be grounded in a variety of factors, from sociodemographics to innate pessimism as a character trait to recent experience. Understanding more about these factors is important: Attempts to boost farmer trials with new varieties rely on an informed targeting and intervention strategy. Table 6 reports on three models that use data from our sample to shed some light

[18]That is, a farmer needs to have volunteered 10% of his land in order to volunteer 100%).

on the question, making use of the survey questions during the elicitation (Models 1 and 2) and also using some data from the 2024 baseline survey (Model 3).

Model 1 uses variables that come closest to personal traits or slow-moving characteristics. There, demographics such as gender and country are highly significant, with both female producers and producers from Mali more likely to be underconfident. The result for gender is in line with previous results that women tend to have less positively biased beliefs in their ability (Niederle and Vesterlund, 2007; Thoma, 2016). Self-image as a farmer also matters significantly: those who consider their rice farming skills and current variety to be below average tend be classified more often as underconfident. The judgment on current varieties is somewhat at odds with the theoretical prediction in Hestermann and Le Yaouanq (2021). One implication of their theory is that underconfident individuals tend to overestimate the quality of their current environment in comparison to alternatively available environments. This implication does not appear to be borne out in our sample, with underconfident producers also believing that their environment, i.e. their current variety, is below average relative to alternative environments. Mirroring the correlational results presented in Table 2, we again find no association between risk attitudes and underconfidence.

Models 2 and 3 augment the analysis by also considering a wider set of variables that captures the household situation. Including these variables does not affect the estimates derived in Model 1. One insight is that individuals that report having experienced higher than average yields in the past growing season tend to be less underconfident as are those with a higher household income over the past six months. The role of these variables in forming underconfidence points to some degree of situativeness and malleability of underconfidence.

F. Robustness Checks

Possible threats to the main findings of the paper come from estimation and measurement issues. Regarding estimation, we first present – in Table 7 – three alternative versions of our main regression. The versions differ in the controls included as well as whether the standard errors were clustered at the village level or not. Model 1 includes neither enumerator nor village controls and standard errors are not clustered at the village level. Model 2 adds enumerator controls and Model 3 village controls. In Model 4, we cluster the standard errors at the village level as well (matching our approach in Table 4). Our main result - that underconfidence is associated with lower WTP for the ARICA experimentation kit - holds across all models, and is in fact stronger when enumerator and village controls are not included.

Table 6: Correlates of Underconfidence

Explanatory variable	**(1)**	**(2)**	**(3)**
Female	0.135**	0.139**	0.120*
	(0.057)	(0.059)	(0.062)
Mali	1.055***	1.077***	0.966***
	(0.266)	(0.264)	(0.285)
Below-average skills	0.262**	0.275**	0.220*
	(0.108)	(0.109)	(0.118)
Above average skills	-0.013	-0.002	-0.004
	(0.041)	(0.041)	(0.041)
Below-average var.	0.263*	0.255*	0.279**
	(0.136)	(0.137)	(0.139)
Among-best var.	-0.055	-0.047	-0.043
	(0.095)	(0.095)	(0.108)
σ	0.104	0.106	0.122*
	(0.068)	(0.068)	(0.071)
α	0.159	0.161	0.140
	(0.111)	(0.114)	(0.127)
λ	-0.008	-0.007	-0.007
	(0.008)	(0.008)	(0.009)
Ambiguity aversion	-0.013	-0.013	-0.007
	(0.014)	(0.014)	(0.015)
Good weather		-0.064	-0.033
		(0.045)	(0.047)
Bad weather		-0.081	-0.065
		(0.080)	(0.087)
Yield deviation		-0.001***	-0.001***
		(0.000)	(0.000)
Age		0.002	0.002
		(0.003)	(0.003)
Growing area (ha)		0.005	0.017
		(0.014)	(0.017)
Food insecure		-0.009	-0.013
		(0.024)	(0.026)
HH income (past month)		0.000	
		(0.000)	
Personal income (past month)		0.000	
		(0.000)	
Bad trial experience			0.001
			(0.079)
Household income (past six months)			-0.003*
			(0.002)
Constant	-0.459***	-0.512**	-0.453**
	(0.080)	(0.201)	(0.224)
Enumerator & village controls	Yes	Yes	Yes
Number of observations	1,957	1,957	1,741
R-squared	0.197	0.199	0.208

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ambiguity aversion measured in 100s FCFA. Average yield is self-reported and measured in tons. Good (bad) weather is self-reported assessment last season's growing conditions. Past-season deviation from average rice production measured in units of 10 bags of rice. Growing area is specific to rice production. Household and personal income measured in thousands of FCFA; six-month household income measured in 100,000s of FCFA. Bad trial experience is specifically with new rice variety.

A second concern regarding estimation is that the main results might be driven by outliers. To address this, we rerun the analysis by excluding rice producers with $A_i^t = 0$ or $A_i^t = 7$, that is who answered either all or none of the confidence questions correctly. We also rerun the analysis by excluding rice producers with highly negative bias (6 or 7). The results are reported in the appendix, Table A.4 as Models 2 and 3. In both cases, the negative correlation of underconfidence with WTP for experimentation remains, and in both cases becomes even stronger.

Measurement of confidence bias has been an topic of ongoing debate for some time now. One key issue is that the difficulty of the questions in the confidence elicitation co-determines the bias measured, a finding that has become known as the 'hard-easy effect'[19] may have shaped or been responsible for our main result (Moore and Healy, 2008). To address possible measurement issues, we first present descriptive statistics for each of the seven questions included in our confidence elicitation. In Table 8 it can be seen that three of the questions were more difficult for the producers in the sample (Questions 2, 6 and 7), and four were easier (Questions 1, 3, 4, and 5). Thus, our questionnaire was not overly easily or overly difficult, but represented a mix of easier and more difficult questions. The classic 'hard-easy' pattern is reproduced in our data - the assessed level of confidence[20] tends to be greater than the actual level of accuracy by question (overestimation) for difficult questions, and less than the actual level of accuracy for easy questions (underestimation).

We then reanalyze our data, controlling for the subjective difficulty of test battery as assessed by each respondent.[21] The key question is whether including difficulty alongside under- and overconfidence changes our main result. Table 9 reports on the coefficient estimates that result from the reanalysis. Models 1 through 3 mirror the corresponding models in Table 4. Two findings emerge. One is that variations in the subjective difficulty of the test battery do not significantly contribute to a better estimate of WTP for experimentation. The other finding is that including subjective difficulty does not substantially affect the contribution of underconfidence to explaining WTP for experimentation.

[19]The 'hard-easy effect' is the finding that hard questions tend to produce overestimation and easy questions tend to produce underestimation.

[20]We asked each producer how sure they were that their response to each question was correct, with options being as sure as unsure (which we code as 50%); sure (60-90%, which we code as 75%); or very sure (90-100%, which we code as 95%); see Appendix 4.

[21]Specifically, it is calculated as the average of participants' stated confidence levels associated with each of the seven questions.

Table 7: Underconfidence and WTE – Robustness to Controls

Explanatory variable	**(1)**	**(2)**	**(3)**	**(4)**
Underconfidence	-29.41***	-27.98***	-23.58***	-23.58***
	(9.038)	(8.775)	(8.905)	(8.638)
Overconfidence	-13.29	-7.363	0.656	0.656
	(10.65)	(10.94)	(11.18)	(11.75)
Underplacement	18.96	19.32	20.55	20.55
	(23.22)	(22.32)	(22.82)	(21.76)
Overplacement	-29.79	10.32	4.847	4.847
	(21.53)	(21.92)	(23.20)	(28.50)
σ	-42.96**	-69.10***	-50.49**	-50.49*
	(19.15)	(22.78)	(23.91)	(29.09)
λ	-1.078	-2.546	-2.471	-2.471
	(3.151)	(3.329)	(3.486)	(3.301)
α	8.340	20.38	34.02	34.02
	(39.58)	(38.53)	(39.22)	(39.89)
Ambig. av. (100s FCFA)	-3.922	-1.172	0.002	0.002
	(4.425)	(4.347)	(4.507)	(4.660)
Below-average skills	-27.68	-12.36	0.860	0.860
	(38.51)	(39.96)	(40.56)	(41.16)
Above-average skills	42.21***	41.00***	39.52***	39.52***
	(13.04)	(13.66)	(14.21)	(13.75)
Stated yield (tons)	0.135***	0.296***	0.491***	0.491***
	(0.052)	(0.103)	(0.126)	(0.105)
Below-average variety	-46.70	-47.88	-24.23	-24.23
	(37.58)	(38.28)	(38.23)	(40.43)
Among-best varieties	72.00***	63.44**	53.36*	53.36*
	(26.21)	(31.57)	(33.91)	(29.51)
Mali	96.57***	287.0***	98.60	98.60
	(21.52)	(71.85)	(152.2)	(75.40)
Female	21.48	9.017	3.403	3.403
	(27.58)	(27.19)	(30.44)	(37.15)
Female $\times$ Mali	-4.726	-70.36*	-54.53	-54.53
	(36.98)	(37.37)	(43.00)	(47.17)
Constant	883.7***	793.1***	800.3***	800.3***
	(42.13)	(79.20)	(135.4)	(93.34)
Enumerator controls	No	Yes	Yes	Yes
Village controls	No	No	Yes	Yes
SEs clustered at village level	No	No	No	Yes
Number of observations	1,957	1,957	1,957	1,957
R-squared	0.043	0.169	0.230	0.230

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Assessed Difficulty and Respondent Performance by Question

Question	No. Correct	% Correct	% Confidence	Difference
Question 1	1829	0.93	0.92	-0.02
Question 2	625	0.32	0.85	0.53
Question 3	1808	0.92	0.90	-0.03
Question 4	1855	0.95	0.90	-0.05
Question 5	1824	0.93	0.88	-0.05
Question 6	1139	0.58	0.71	0.13
Question 7	1139	0.58	0.72	0.14

5. Conclusion

The economic consequences of biased beliefs in one's abilities are well documented for overconfident individuals, but surprisingly little is known about the consequences for underconfident individuals. Guided by recent theoretical work on the link between confidence bias and purposeful experimentation, we empirically investigate this link by examining the full distribution of confidence bias and its impact on demand for experimentation, including for negatively biased individuals. To add contextual heft, we choose a setting in which experimentation is not just a prerequisite for productivity improvements, but essential for maintaining livelihoods. In such a setting, negative confidence bias could conceivably have important consequences for households.

Adapting established techniques for measuring confidence to the study context, we present novel evidence that confidence bias matters for an individual's demand for experimentation. In particular, it is underconfidence, measured as underestimation, that reveals itself as the main driver of the average effect. This link between confidence and experimentation turns out to be consequential in our context. Underconfident smallholders who are offered the opportunity to experiment with climate-resilient rice varieties are willing to pay significantly less for this option than their unbiased and overconfident counterparts. In turn, the share of farmers ending up without climate-resilient seed material provided at cost is 10 percent higher among the underconfident, locking them out of the technology adoption process. Dynamically, this could set into motion deleterious dynamics: we find that confidence bias is negatively affected by bad harvests, which is made more likely among farmers opting out of the adoption of new crop varieties.

Table 9: Confidence, Difficulty, and Willingness to Experiment

Explanatory variable	(1)	(2)	(3)
Underconfidence	-22.66**	-22.89***	-22.40**
	(8.774)	(8.632)	(8.621)
Overconfidence	-2.037	-0.666	-1.677
	(10.42)	(11.61)	(11.69)
Assessed Difficulty	251.0	251.9	211.2
	(163.6)	(159.8)	(160.8)
Underplacement		15.78	20.90
		(21.45)	(21.63)
Overplacement		5.211	6.899
		(28.38)	(28.21)
σ		-56.27*	-50.42*
		(28.98)	(29.11)
λ		-2.506	-2.518
		(3.273)	(3.314)
α		30.52	34.07
		(40.35)	(39.96)
Ambiguity av. (100s FCFA)		-0.342	-0.205
		(4.592)	(4.636)
Below-average skills			2.379
			(41.49)
Above-average skills			39.15***
			(13.69)
Stated yield, tons			0.493***
			(0.105)
Below-average variety			-23.95
			(40.56)
Among-best varieties			50.94*
			(29.26)
Mali			92.24
			(74.87)
Female			5.925
			(37.06)
Female $\times$ Mali			-55.94
			(46.94)
Constant	609.8***	639.5***	613.4***
	(143.6)	(166.8)	(176.5)
Enumerator and village controls	Yes	Yes	Yes
Number of observations	1,957	1,957	1,957
R-squared	0.221	0.224	0.231

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Mean WTP: 907 FCFA; Median WTP: 1000 FCFA.

Our results from the field are derived against the background of climate change, which negatively affects the productivity of existing environments. The patterns uncovered in this context may well generalize to other settings affected by trends such as deindustrialization or decarbonization, in which adherence to existing assets and practices is associated with declining productivity. Likewise, they are also likely to have relevance for sectors, such as those affected by AI, in which rewards for experimentation are large, leading to a widening gap in welfare between those who experiment and do not. This could make identifying individuals who are less likely to experiment a meaningful new focus for policy because these individuals can be expected to be less successful in an era of rapid change.

A natural question raised by our results is: if underconfidence is an important behavioral distortion reducing experimentation (and thus adaptation), do effective interventions exist that could either reduce the underestimation of underconfident individuals, or help to facilitate their experimentation in spite of their underconfidence? Some portion of over- or underconfidence may be hereditary (Johnson and Fowler, 2011). Recent evidence from neuroscience and psychology, on the other hand, has shown that levels of underconfidence can be affected through feedback (Katyal et al., 2025). Such interventions could take the form of cognitive behavioral therapy (Blattman et al., 2017), which has been shown to have long-lasting positive effects (Blattman et al., 2023), or other strategies such as self-efficacy training (McKelway, 2025). These measures await rigorous evaluation in the field.

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Supplementary Appendix

A1. Tables

Table A1. Descriptive statistics by country.

Variable	Pooled Mean	Mali Mean	Côte d'Ivoire Mean
Confidence-related Variables			
Confidence	0.08	0.02	0.15
Overconfident	0.42	0.42	0.43
Underconfident	0.35	0.33	0.36
Underplacement	0.24	0.22	0.27
Overplacement	0.40	0.42	0.38
Number of answers correct	5.22	5.56	4.87
Considers rice cultivation skills below average	0.05	0.04	0.07
Considers rice-cultivation skills better than average	0.56	0.50	0.62
Considers current variety below average	0.05	0.03	0.07
Considers current variety among the best	0.17	0.13	0.21
Other Behavioral Parameters			
σ	0.70	0.71	0.69
α	0.72	0.74	0.71
λ	2.73	2.74	2.72
Ambiguity aversion	48.95	75.60	21.22
Producer & Farm Characteristics			
Female	0.319	0.361	0.276
Age	47.04	48.83	45.18
Rice area cultivated (ha)	1.789	1.268	2.332
Personal income, past month (1000s FCFA)	151.01	63.04	242.55
Number of Observations	1,957	959	998

Table A2. Confidence levels & demand for experimentation with ARICA

Explanatory variable	
Underconfidence (1)	-12.37
	(25.44)
Underconfidence (2)	-113.6***
	(34.95)
Underconfidence (3)	-122.2**
	(49.80)
Underconfidence (4)	-110.7*
	(63.42)
Underconfidence (5)	163.9
	(240.0)
Underconfidence (6)	-127.3
	(102.0)
Underconfidence (7)	-59.24
	(144.1)
Overconfidence (1)	-21.52
	(24.02)
Overconfidence (2)	9.997
	(35.74)
Overconfidence (3)	-12.68
	(48.25)
Overconfidence (4)	30.14
	(79.91)
Overconfidence (5)	-12.75
	(213.3)
Underplacement	24.49
	(23.02)
Overplacement	-1.841
	(28.20)
σ	-45.04
	(28.98)
λ	-1.829
	(3.342)
α	32.17
	(41.10)
Ambiguity aversion (100s FCFA)	-0.703
	(4.715)
Considers rice cultivation skills below average	1.788
	(40.66)
Considers rice-cultivation skills better than average	38.57***
	(13.69)
Stated average yield, tons	0.515***
	(0.113)
Considers current variety below average	-22.19
	(41.44)
Considers current variety among the best	51.32*
	(29.76)
Mali	124.6
	(77.55)
Female	6.039
	(36.67)
Female x Mali	-54.49
	(46.67)
Enumerator and village controls	Yes
Number of Observations	1,957
R-squared	0.236

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Mean WTP: 906 FCFA; Median WTP: 1000 FCFA.

Table A3. Underconfidence & demand for experimentation, by country

Explanatory variable	Pooled Sample	Mali	Côte d'Ivoire
Underconfidence	-23.58***	-25.27**	-21.50*
	(8.638)	(12.12)	(12.05)
Overconfidence	0.656	-7.925	7.367
	(11.75)	(17.05)	(15.77)
Underplacement	20.55	-23.46	64.01**
	(21.76)	(32.21)	(30.54)
Overplacement	4.847	-41.76	47.82
	(28.50)	(33.85)	(44.31)
σ	-50.49*	-11.30	-68.25*
	(29.09)	(39.69)	(38.82)
λ	-2.471	-2.488	-1.760
	(3.301)	(5.494)	(4.123)
α	34.02	-57.55	161.7***
	(39.89)	(57.05)	(48.47)
Ambiguity aversion (100s FCFA)	0.002	-4.513	8.738
	(4.660)	(6.105)	(7.574)
Considers rice cultivation skills below average	0.860	59.41	-26.55
	(41.16)	(76.42)	(47.46)
Considers rice-cultivation skills better than average	39.52***	47.10**	32.19*
	(13.75)	(20.58)	(19.06)
Stated average yield, tons	0.491***	0.494***	-2.097
	(0.105)	(0.106)	(18.52)
Considers current variety below average	-24.23	-81.35	4.263
	(40.43)	(84.42)	(41.09)
Considers current variety among the best	53.36*	46.36	56.43
	(29.51)	(44.09)	(37.71)
Mali	98.60		
	(75.40)		
Female	3.403	-58.22*	-3.134
	(37.15)	(29.72)	(37.08)
Female x Mali	-54.53		
	(47.17)		
Enumerator and village controls	Yes	Yes	Yes
Number of Observations	1,957	1,957	1,957
R-squared	0.230	0.209	0.252

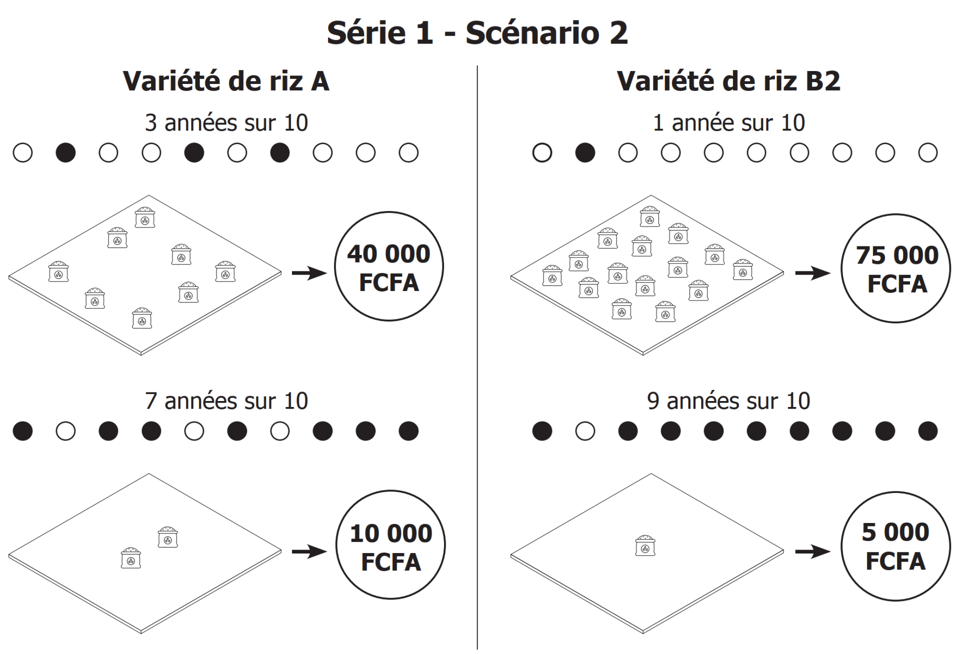
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Pooled Sample: Mean WTP = 906 FCFA; Median WTP = 1000 FCFA. Mali: Mean WTP = 948 FCFA; Median WTP = 1000 FCFA. Côte d'Ivoire: Mean WTP = 865 FCFA; Median WTP = 1000 FCFA.

Table A4. Underconfidence & demand for experimentation, with extreme values excluded

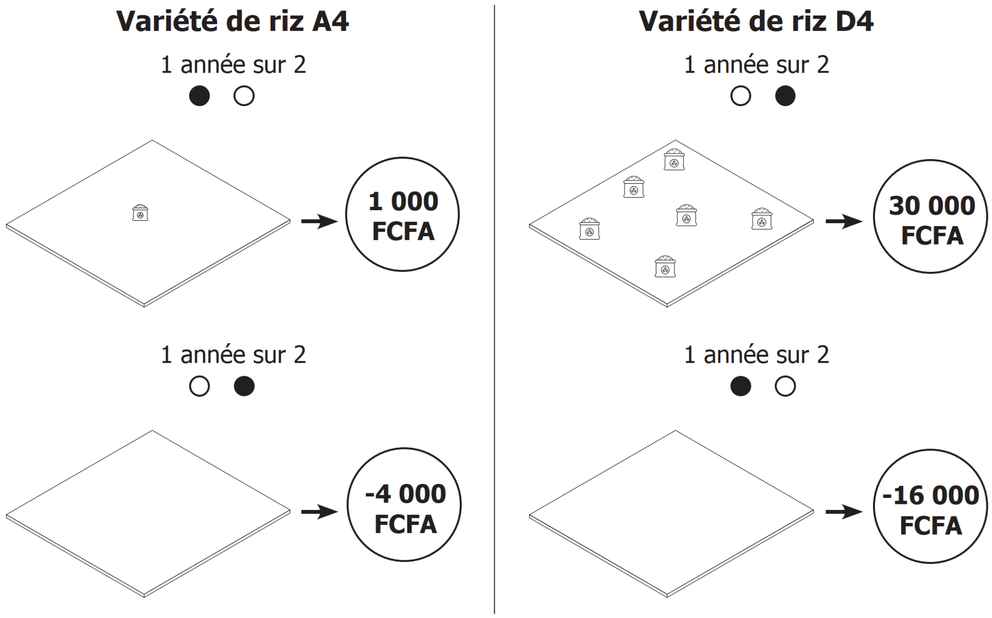
Explanatory variable	Model 1	Model 2	Model 3
Underconfidence	-23.58***	-28.29**	-29.32***
	(8.638)	(11.06)	(11.10)
Overconfidence	0.656	3.213	0.367
	(11.75)	(12.75)	(12.01)
Underplacement	20.55	13.82	24.83
	(21.76)	(29.90)	(21.98)
Overplacement	4.847	-0.374	1.986
	(28.50)	(31.38)	(28.33)
σ	-50.49*	-53.54*	-50.06*
	(29.09)	(31.62)	(29.01)
λ	-2.471	-2.405	-2.183
	(3.301)	(3.524)	(3.316)
α	34.02	18.48	36.29
	(39.89)	(42.93)	(40.34)
Ambiguity aversion (100s FCFA)	0.002	1.865	-0.046
	(4.660)	(5.265)	(4.692)
Considers rice cultivation skills below average	0.860	19.45	0.293
	(41.16)	(44.06)	(41.18)
Considers rice-cultivation skills better than average	39.52***	28.39*	38.47***
	(13.75)	(14.94)	(13.70)
Stated average yield, tons	0.491***	10.49	0.494***
	(0.105)	(10.46)	(0.106)
Considers current variety below average	-24.23	-33.76	-26.75
	(40.43)	(45.19)	(40.65)
Considers current variety among the best	53.36*	44.89	47.17
	(29.51)	(32.39)	(30.25)
Mali	98.60	169.5*	77.48
	(75.40)	(89.87)	(74.63)
Female	3.403	4.695	2.459
	(37.15)	(37.57)	(36.71)
Female x Mali	-54.53	-90.97	-46.91
	(47.17)	(56.10)	(46.27)
Enumerator and village controls	Yes	Yes	Yes
Number of Observations	1,957	1,649	1,939
R-squared	0.230	0.227	0.228

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Mean WTP = 906 FCFA; Median WTP = 1000 FCFA. Model 1 presents our main baseline regression; Model 2 presents the same regression while excluding producers who answered either 0 or 7 answers correct; and Model 3 excludes producers with an underconfidence score of 6 or 7.

A2. Examples of Diagrams shown for the Elicitation of Producer Prospect Theory Parameters



Série 3 - Scénario 4



A3. ARICA experimentation kit

A4. Questionnaire

EXPERIMENT QUESTIONNAIRE – 2025

Note to the interviewer: Please read the above information about the study to the producer and obtain his/her consent before the interview.

Good day. We are from AfricaRice and we would like to invite you to participate in research about producer experimentation with new drought-tolerant rice varieties. This research is funded by the Van Vliet Research Fund and represents a research collaboration between the University of Saskatchewan in Canada, AfricaRice, the University of Heidelberg (Germany), the Centre national de recherche agronomique (CNRA), the Université Alassane Ouattara de Bouaké, and Institut d'Economie Rurale (Mali). The research has been approved on ethical grounds by the University of Saskatchewan Behavioral Research Ethics Board.

The interview should take approximately 30 minutes to 1 hour, and we will ask you questions about several topics including your risk preferences and information about the rice variety you cultivate. You may receive the opportunity to experiment with a small amount of seed of a new ARICA rice variety. If you receive the ARICA rice seed, we will ask you to experiment with it over the coming growing season and plant it in your plot next to the rice variety that you currently cultivate, and provide us with information about which of the two varieties you prefer after the harvest, when we will return for a follow-up interview.

The interviewer should pause after reading the second paragraph, and then ask:

"Do you accept to participate in our study? Would you like to hear more details about what participation would entail?"

We will maintain the data we have collected securely and confidentially and no information that could be used to identify you personally such as your name, telephone number or income information will be made public. The data will be stored securely for an indefinite time period but at least seven years after the study results are published on institutional computer-based secure storage systems of the researchers such as OneDrive at AfricaRice, IER, the University of Heidelberg, and the University of Saskatchewan. Findings from the data will be disseminated in reports and publications where data will only be reported in aggregate form or anonymized. By participating in this study, you will benefit by potentially gaining access to seed of new, advanced rice varieties, while there are no anticipated risks associated with your participation. You are free to withdraw from the study at any point without penalty by calling the number on the card we will provide you with, after which we will destroy your data. If you are selected to participate in our study, your data will be used for analysis as part of this study, and in the future, it is possible that the data collected as a result of the survey is made public by putting it in a research data repository where others can access and use the data for their own research purposes (anonymously, with no confidential information such as name or phone number shared).

If you are selected to participate in our study, would you agree to the data collected being used for analysis as part of this study? (1 = Yes ; *0* ***= No)***

You may contact Mr. Rachidi ABOUDOU at +225XXXXXXXX if you no longer wish to participate in this study. Your data will then be deleted from the server.

Interviewer : (If **Yes**, before beginning section 1, **the interviewer should provide** a voucher of **1000 FCFA to the producer** and state: "As part of your participation in this experiment, we are now providing you with **1000 FCFA**, and you may receive additional compensation after participating in an experimental task. You may withdraw from the study at any point without penalty, after which we will destroy your data, and you may leave with any money that you have received up until the point at which you decide to withdraw.*"*

INTRODUCTION AND CONSENT

NB: For the interviewers: record the geographic coordinates of the location of each interview.

SECTION 1.A : PRELIMINARY INFORMATION

Questions	**Answers**
1.1. Code of the respondent	
1.2 What is your name (first name and family name) ?	
1.3 Gender of producer (**Code 1)**	**Code 1:** *1=Female ; 0=Male*
1.4 A. Country name (**Code 2)**	**Code 2:** *1=Côte d'Ivoire ; 2=Mali*
1.4 B. Region	
1.4 C. Village	
1.5 Date of the survey	
1.6 Family name and first name of interviewer	
1.7 Language of interview (code 4)	
1.8 Do you decide which rice varieties are grown on your rice plots?	
1.9 A. Have you already started cultivating (plant nursery, etc) for this growing season?	
1.9 B. When do you plan to start cultivating (plant nursery, preparation of soil,. etc) for the next growing season?	
1.9 C. When do you plan to start transplanting or sowing (broadcasting, etc.) for the next growing season?	
1.10 How long after transplanting do you usually harvest? (*Specify number of months*)	
1.11 How many years have you been growing rice (owning a rice plot)?	___ *years.*
1.12 A. What rice variety (or varieties) do you plan to use for this season? (list by plot) ?	
1.12 B. How do you classify them (Code) ?	**Code**: *1= Improved, 2= Not improved*
1.12 C. Among the rice varieties grown in your village, how would you rate the performance of your current variety(ies) on your plots, compared with the other varieties?	**Code**: *1 = Among the best, 2 = Above average, 3 = Average, 4 = Below average, 5 = Among the worst*
1.12 D. Among the rice varieties in your region, how would you rate the performance of your current variety(ies) on your plots, compared with the other varieties?	**Code**: *1 = Among the best, 2 = Above average, 3 = Average, 4 = Below average, 5 = Among the worst*
1.13 For how many years have you used your current rice variety/varieties?	
1.14 How much total rice seed will you use to plant on your plots (kgs)? (list by plot and by variety if multiple in use) (by ha)	

1.15 What is the nature of the seed?	Code : *1=Saved seed; 2=Purchased seed; 3=Seed provided by another farmer*
1.15 : If „Purchased seed“ or „Seed provided by another farmer“: what is the source of the rice seed?	***Code****: 1 = Village market; 2 = Market outside the village; 3 = Village producer; 4 = Producer outside the village*
1.16 A. How interested are you in obtaining a new rice variety to improve your production?	***Code*** *: 0=Not interested at all; 1=Not interested; 2=Neutral 3=Interested; 4=Very interested*
1.16 B. In your opinion, what are the main characteristics that a good rice seed should have to meet your expectations and guarantee good production on your plot? Please indicate the three main characteristics you would appreciate in a potential new rice variety to use on your plot, in order of importance.	*1. Good yield 2. Aromatic 3. Disease resistant 4. Drought resistant 5. Flood resistant 6. Good grain quality (size, color, texture) 7. Short production cycle (early maturity) 8. Good tillering capacity (more stems per plant) 9. Tolerant to poor soils (salinity, acidity) 10. Good post-harvest storage 11. Suited to local market preferences 12. Affordable seed price 99- Other (please specify))*
1.17 C. In your rice production, what do you think are the most important factors in obtaining a good harvest (list the 3 most important in order of importance)?	***Code****: 1- the producer's skills 2- inputs (seeds, fertilizers, etc.) 3- luck or bad luck 4- God's will 5- compliance with religious rules 6- soil quality (soil fertility, texture, etc.) 7- Access to water (irrigation, rainfall) 8- Climatic conditions (rain, temperature, drought) 9- Disease and pest control 10- Access to agricultural equipment (tractors, threshing machines, etc.) 11- Financing or access to credit 12- Technical support (agricultural advice, training) 13- Availability of labor 14- Planning of the agricultural calendar (right time to sow and harvest) 15- The variety of rice you grow 99- Other (please specify)*
1.17 d. Do you use direct seeding or do you first go through a nursery and then transplant the seedlings into the rice field?	***1****= Direct seeding, 2= Nursery + transplanting*
1.18 A. Are you considering buying seed of a new rice variety that you haven't used before this season?	*1=Yes ; 0=No*

1.18 B. If Yes, which variety? (if more than one, list all)	*Open-ended*
1.19. Where do you plan to buy rice seed? (If other producer, list name)	
1.20 A. On how many hectares of land do you grow rice?	____*hectares.*
1.20 B. Access to the land on which you produce rice	***Code*** *: 1= Owner (land purchased or inherited); 2= Lease; 3=Rental; 4=Sharecropping; 99: Other (please specify))*
1.20 C. Total rice production in the household during the last growing season (in 100 kg bags)??	____ *100 kg bags.*
1.20 D. How much rice did the household sell during the last growing season (in 100 kg bags)?	____ *100 kg bags.*
1.20 E. What is the value of the rice sold by the household during the last growing season (in 100 kg bags)?	____ *FCFA*
1.20 F. How much rice did the household consume during the last growing season (in 100 kg bags)?)	____ *100 kg bags.*
1.20 G. How do you rate the weather conditions during the last rice-growing season?	***Code*** *: 1 = perfect, 2 = good, 3 = average, 4 = bad, 5 = very bad.*
1.20 I. How do you rate your rice-growing skills compared with those of other farmers in the village?	***Code*** *: 1 = Among the best, 2 = Above average, 3 = Average, 4 = Below average, 5 = Among the worst*
1.21 What was your household's income from agriculture in the last month?	____ *FCFA*
1.22 What was your personal income from agriculture in the last month?	____ *FCFA*
1.23 What was your household's income last month from non-agricultural activities?	____ *FCFA*
1.24 What was your personal income last month from non-agricultural activities?	____ *FCFA*
1.25 In the last 7 days, if you have not had enough food or money to buy food, how often has your household had to borrow food or rely on help from friends or relatives?	*Frequency (0-7 – number of days per week)*
1.26 In the last 7 days, if you haven't had enough food or money to buy food, how often has your household had to limit adults' consumption so that young children could eat?	*Frequency (0-7 – number of days per week)*
1.27 Do you think this rice growing season will be good or bad in terms of weather?	*1) Very sure it will be good; 2) I think it will be good; 3) I'm not sure; 4) I think it will be bad; 5) I'm sure it will be bad*
1.29 B) If Yes, what is your (or a relative's) phone number?	

Code 4 *: 1= Malinké/Dioula, 2=* Baoulé, *3=* Sénoufo , *4=* Agni, *5=* Bété, *6=* Guéré, *7=* Yacouba, *8 =* Attié, *9=* French, *10= Other (please specify)*

SECTION 1. B : CONFIDENCE

1.26A-1 We have seven questions on your perceptions of the climate and rice growing. 1. In your opinion, how does the sun rise and set?	***Code** : 1 = The sun rises and sets on the same side, 2 = The sun rises on one side and sets on the other.*
1.26A-2 Do you think your answer is correct?	***Code** : 1= Very sure (90-100%), 2 = Sure (60-90%), 3 = As Sure as Not sure (50%/50%).*
1.26B- Which city receives more rainfall per year, on average: Sikasso, or Bouake?	***Code** : 1= Sikasso, 2 = Bouake*
1.26B-2 Do you think your answer is correct??	***Code** : 1= Very sure (90-100%), 2 = Sure (60-90%), 3 = As Sure as Not sure (50%/50%).*
1.26C-1 In your opinion, is it better to weed the rice field before or after applying fertilizer?	***Code** : 1 = Before, 2 = After.*
1.26C-2 Do you think your answer is correct?	***Code** : 1= Very sure (90-100%), 2 = Sure (60-90%), 3 = As Sure as Not sure (50%/50%).*
1.26D-1 Fertilizers can improve the harvest. In your opinion, is it better to apply urea first then NPK fertilizer or NPK fertilizer first then urea when producing rice?	***Code :** 1 = first urea, 2 = first NPK fertilizer*
1.26D-2 Do you think your answer is correct??	***Code** : 1= Very sure (90-100%), 2 = Sure (60-90%), 3 = As Sure as Not sure (50%/50%).*
1.26E-1 Herbicides can improve the harvest. In your opinion, is it better to apply herbicides earlier or later in the rice growing season?	***Code** : 1 = Earlier, 2 = Later.*
1.26E-2 Do you think your answer is correct??	***Code** : 1= Very sure (90-100%), 2 = Sure (60-90%), 3 = As Sure as Not sure (50%/50%).*
1.26F-1 RiceAdvice is a decision support tool to help rice producers in Africa. Is its main objective:	***Code :** 1 = To help choose which variety of rice to grow? 2 = To provide management recommendations for fertilizer application ?*
1.26F-2 Do you think your answer is correct??	***Code** : 1= Very sure (90-100%), 2 = Sure (60-90%), 3 = As Sure as Not sure (50%/50%).*
1.26G-1 Is the System of Rice Intensification (SRI) a rice growing technique that:	***Code** : 1 = Involves using more fertilizer to increase yields? 2 = Is based on reducing inputs (fertilizer and seeds), with wider spacing between plants, which generally leads to higher yields?*

1.26G-2 Do you think your answer is correct??	***Code** : 1 Very sure (90-100%), 2 = Sure (60-90%), 3 = As Sure as Not sure (50%/50%).*
1.26H How many of your 7 answers in this section of the questionnaire do you think are correct (0, 1, 2, 3, 4, 5, 6, 7)?	***Code** : 0, 1, 2, 3, 4, 5, 6, or 7.*
1.26I Other rice producers in this village answer these 7 questions (from this module). Think about the average producer. Do you think you have more or fewer correct answers than the average producer?	***Code** : 1= More correct answers, 2 =As many correct answers, 3 = Fewer correct answers.*

SECTION 2 : RISK AVERSION

Question 2.1 : (*Series 1 : Scenario 1 to 14*)

The interviewer should read the following:

Imagine you had to choose between **two varieties of rice**. One produces **low yields**, but these are **more regular from one year to the next**. The second variety sometimes produces **very high yields**, but only when **conditions are right.** We'd like to know which rice variety you'd prefer in the following scenarios. Choosing variety B over variety A means getting higher yields in years when conditions are good, but also risking lower yields when conditions are not favorable.

At the end of our exchange, after another section, you'll receive a monetary reward based on your answers to these risk-related questions. Specifically, one of your decisions will be drawn for an actual payout as a percentage of the numbers shown, using a random device with equal probability for each decision task to be extracted. **So think carefully before making your choice**.

{NB: The interviewer must read the questions below until the farmer chooses variety B. If he/she chooses variety B in **question 2.1.1**, the interviewer can move on to the next question (**2.2**)}.

A) Rice variety A – three years out of ten the paddy rice produced is worth **40 000 FCFA** if sold after the harvest; seven years out of ten the paddy rice produced is worth **10 000 FCFA** if sold after the harvest.
B) Rice variety B – one year out of ten, the paddy rice produced is worth ___x____ FCFA if sold after the harvest; nine years out of ten, the paddy rice produced is worth **5,000 FCFA** if sold after the harvest.
2.1-1. x = 68 000 FCFA **2.1-2.** x = 75 000 FCFA; **2.1-3.** x = 83 000 FCFA; **2.1-4.** x = 93 000 FCFA;
2.1-5. x = 106 000 FCFA **2.1-6.** x = 125 000 FCFA; **2.1-7.** x = 150 000 FCFA. **2.1-8.** x = 185 000 FCFA.
2.1-9. x = 220 000 FCFA **2.1-10.** x = 300 000 FCFA **2.1-11.** x = 400 000 FCFA. **2.1-12.** x = 600 000 FCFA.
2.1-13. x = 1 000 000 FCFA. **2.1-14.** 1 700 000 FCFA

2.1.1. The interviewer should specify for what value of x the farmer has chosen "B" for the first time.
Answer: ______.

Question 2.2 (*Series 2: Scenario 1 to 14*)

We will now ask you a series of similar questions. {NB: the interviewer must read the questions below until the farmer chooses variety C. If he/she chooses variety B in **question 2.2.1**, the interviewer can move on to the next question (**2.3**)}.

A) Rice variety A – nine years out of ten the paddy rice produced is worth **40 000 FCFA** if sold after the harvest; one year out of ten the paddy rice produced is worth **30 000 FCFA** if sold after the harvest.

B) Rice variety C – seven years out of ten, the paddy rice produced is worth ___x____ FCFA if sold after the harvest; three years out of ten, the paddy rice produced is worth **5 000 FCFA** if sold after the harvest.

2.2-1. x = 54 000 FCFA **2.2-2.** x = 56 000 FCFA; **2.2-3.** x = 58 000 FCFA; **2.2-4.** x = 60 000 FCFA;
2.2-5. x = 62 000 FCFA **2.2-6.** x = 65 000 FCFA; **2.2-7.** x = 68 000 FCFA. **2.2-8.** x = 72 000 FCFA.
2.2-9. x = 77 000 FCFA **2.2-10.** x = 83 000 FCFA **2.2-11.** x = 90 000 FCFA. **2.2-12.** x = 100 000 FCFA.
2.2-13. x = 110 000 FCFA **2.2-14.** 130 000 FCFA

2.2 The interviewer should specify for what value of x the farmer has chosen "B" for the first time.

Answer: ______.

Question 2.3 : (*Series 3: Scenario 01 to 07*)

Now we're going to ask you another set of similar questions. Let's suppose you find yourself in a scenario where both varieties fail **every other year**, and you can lose the money invested in farm inputs in the event of a poor harvest. Choosing variety D over variety A means **higher yields** in years when **conditions are good**, but it also means risking **greater losses** when conditions aren't favorable. Please tell us whether you would choose variety A or D in the following scenarios.

{NB: the interviewer must read the questions below until the farmer chooses variety B. If he/she chooses variety D in **question 2.3.1**, the interviewer can move on to the next section of the questionnaire}.

2.3-1 A) **Rice variety A**: one year out of two you produce paddy rice worth **25 000 FCFA** if sold after the harvest; one year out of two you will lose **4 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

B) **Rice variety D**: one year out of two you produce paddy rice worth **30 000 FCFA** if sold after the harvest; one year out of two you will lose **21 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

2.3-2 A) **Rice variety A**: one year out of two you produce paddy rice worth **4 000 FCFA** if sold after the harvest; one year out of two you will lose **4 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

B) **Rice variety D**: one year out of two you produce paddy rice worth **30 000 FCFA** if sold after the harvest; one year out of two you will lose **21 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

2.3-3 A) **Rice variety A**: one year out of two you produce paddy rice worth **1 000 FCFA** if sold after the harvest; one year out of two you will lose **4 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

B) **Rice variety D**: one year out of two you produce paddy rice worth **30 000 FCFA** if sold after the harvest; one year out of two you will lose **21 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

2.3-4 A) **Rice variety A**: one year out of two you produce paddy rice worth **1 000 FCFA** if sold after the harvest; one year out of two you will lose **4 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

B) **Rice variety D**: one year out of two you produce paddy rice worth **30 000 FCFA** if sold after the harvest; one year out of two you will lose **16 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

2.3-5 A) **Rice variety A**: one year out of two you produce paddy rice worth **1 000 FCFA** if sold after the harvest; one year out of two you will lose **8 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

B) **Rice variety D**: one year out of two you produce paddy rice worth **30 000 FCFA** if sold after the harvest; one year out of two you will lose **16 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

2.3-6 A) **Rice variety A**: one year out of two you produce paddy rice worth **1 000 FCFA** if sold after the harvest; one year out of two you will lose **8 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

B) **Rice variety D**: one year out of two you produce paddy rice worth **30 000 FCFA** if sold after the harvest; one year out of two you will lose **14 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

2.3-7 A) **Rice variety A**: one year out of two you produce paddy rice worth **1 000 FCFA** if sold after the harvest; one year out of two you will lose **8 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

B) **Rice variety D**: one year out of two you produce paddy rice worth **30 000 FCFA** if sold after the harvest; one year out of two you will lose **11 000 FCFA** (that is to say, losses net of the costs of agricultural inputs purchased).

2.3 The interviewer should specify for which question the farmer has chosen “D” for the first time. Answer: ______.

<u>Question 2.4</u>:

2.4.0 A. **On average, over all the cropping seasons, how many 100 kg bags of rice do you generally harvest from all your plots with the rice varieties you currently grow?**

The interviewer should read the following to the rice farmer:

Now imagine another situation in which you have the choice between continuing to grow only your own variety (variety A) or partially or fully growing another new variety for the upland ecology (variety B), which has been selected to be drought tolerant and disease resistant and optimised for rainfed production (upland ecology).

This new variety (Variety B) has demonstrated, in field trials, an average yield of **27-29 bags (of 100 kg each)** per hectare; however, it is not known exactly what yields this would provide on your plot, in your current growing environment (with the practices you currently use).

By way of comparison, based on your previously declared rice-growing area (question 1.25B) and your answer on the total number of bags harvested (question 2.4-0A), your current variety of rice produces approximately ____100 kg bags per hectare.

2.4-1 If you had the choice between option 1) growing only your current variety on the plot, or option 2) growing your current variety on 90% of your plot and the new variety (Variety B) on 10% of your plot, which option would you choose?

2.4-1A : *The interviewer should indicate the choice of the producer,either option 1 or option 2:* ________.

If the producer chooses Option 1, the interviewer should ask the following:

"Is there a hypothetical new variety (as described for Variety B) for which you would select Option 2, if it had a higher average yield than the new variety described here?"

2.4-1B *Answer: Yes/No.*

If yes, the interviewer should ask the following: "What would be the minimum average yield of the variety for you to devote 10% of your plot to its cultivation if you had never grown it before?"

2.4-1C : Answer – Minimum average yiels (in bags of 75kg/ha): ______.

2.4-2 If you had a choice between option 1) growing only your current variety on the plot, or option 2) growing your current variety on 50% of your plot and the new variety (Variety B) on 50% of your plot, which option would you choose?

2.4-2A : *The interviewer should indicate the choice of the producer, either option 1 or option 2:* ________.

If the producer chooses Option 1, the interviewer should ask the following:

"Is there a hypothetical new variety (as described for Variety B) for which you would select Option 2, if it had a higher average yield than the new variety described here?"

2.4-2B *Answer : Yes/No.*

If yes, the interviewer should ask the following: "What would be the minimum average yield of the variety for you to devote 50% of your plot to its cultivation if you had never grown it before?"

2.4-2C : Answer – Minimum average yield (in bags of 75kg/ha): ______.

2.4-3 If you had the choice between option 1) growing only your current variety on the plot, or option 2) growing the new variety (Variety B) on 100% of your plot, which option would you choose?

2.4-3A : *The interviewer should indicate the choice of the producer, either option 1 or option 2:* ________.

If the producer chooses Option 1, the interviewer should ask the following:

"Is there a hypothetical new variety (as described for Variety B) for which you would select Option 2, if it had a higher average yield than the new variety described here?"

2.4-3B *Answer: Yes/No.*

If yes, the interviewer should ask the following: "What would be the minimum average yield of the variety for you to devote 100% of your plot to its cultivation if you had never grown it before?"

2.4-3C : Answer – Minimum average yield (in bags of75kg/ha): ______.

Next :
2.4-4 If the producer selected Option 1 for any of the previous three questions, the interviewer should ask the producer why he/she selected Option 1 (open-ended answer). Answers should be split out for each of the 3 scenarios in separate columns (N/A for the question if the producer selected Option 2).

2.4-4A : _________________.

2.4-4B : _________________.

2.4-4C : _________________.

Question 2.5:

The interviewer should begin by saying : *"Now, we are going to move to a section of the interview meant to better understand how you make decisions when the probability of outcomes is known and when it is ambiguous. This is not a game, but rather an experimental elicitation of your preferences – however, there will be the opportunity to obtain a real return for your participation.*

We'd like to know how much you'd be prepared to pay for two different options. In the first possibility, there is a bag containing 05 white balls and 05 black balls. (The interviewer shows the bag and pours out the balls for the producer to see before putting them back in the bag). You will choose a colour, white or black, and then you will have the chance to take a ball out of the bag. If it's the same colour as the one you've chosen, you'll receive 1000 FCFA. We'd like to know how much you'd be prepared to pay (0 - 1000 FCFA) to be able to take the ball out of the bag. The more you are prepared to pay, the more likely you are to be able to get a ball out of the bag.

Second possibility: there is a bag with 10 balls (white and black balls), but you don't know how many of each colour there are. You will choose a colour and then have the chance to draw a ball from the bag, as before, and if it is the same colour as the one you chose, you will receive 1000 FCFA. However, this time you won't know the probability of drawing a ball of a certain colour. We'd like to know how much you'd be prepared to pay (0 - 1000 FCFA) for the chance to get the ball out of the bag. If you are prepared to pay more, the chance that you will be able to get a ball out of the bag will be higher.

The interviewer should read the following sentence to the producer: "To start with, we're going to explain how the experiment works, using a bag of fertiliser as an example." *The farmer can choose one of the following values: 0, 50, 100, 200, 300, 400, 500, 600, 700, 800, 900, 1,000, each corresponding to a different throw of the dice (50 = 2, 100 = 3, 200 = 4, 300 = 5, 400 = 6, 500 = 7, 600 = 8, 700 = 9, 800 = 10, 900 = 11, 1 000 = 12).*

The producer is not willing to wager any money: 0 FCFA ○
Dice roll= 2 : 50 FCFA ○
Dice roll= 3 : 100 FCFA ○
Dice roll= 4 : 200 FCFA ○
Dice roll= 5 : 300 FCFA ○
Dice roll= 6 : 400 FCFA ○
Dice roll= 7 : 500 FCFA ○
Dice roll= 8 : 600 FCFA ○
Dice roll= 9 : 700 FCFA ○

Dice roll= 10 : 800 FCFA
Dice roll= 11 : 900 FCFA
Dice roll= 12 : 1000 FCFA

3B.1 Specify the amount chosen by the producer (WTP) to pay for the fertiliser (Amount on the dice roll list above)
3B.2 Specify the amount of the dice roll associated with the amount chosen by the producer
3B.3 What is the result of the two dice? NB: Add up the numbers on the two dice.
3B.4 What is the amount corresponding to the results of the dice (in FCFA)?
3B.5 Will the producer receive the fertiliser hypothetically? (1=Yes; 0= No)

Now we're going to do the experiment itself. *Having explained this experimental procedure, the interviewer must then explain that a coin will be tossed to determine which of these two scenarios the BDM will be run for and ask the producer for his WTP for each.*

After you've told us how much you'd be willing to pay for each opportunity, and after you've completed the rest of the experiment, we'll then move on to one of these scenarios, and depending on your declared willingness-to-pay value and the roll of the dice, you may have the chance to win 1 000 FCFA by choosing a ball from one of the two bags.

2.5-1 *"How much would you be prepared to pay to take one ball out of the bag containing 05 white and 05 black balls?"*

The producer can choose one of the following values for 2.5-1:

The producer is not willing to wager any money: 0 FCFA
50 FCFA
100 FCFA
200 FCFA
300 FCFA
400 FCFA
500 FCFA
600 FCFA
700 FCFA
800 FCFA

900 FCFA

1000 FCFA

***2.5-2** If the producer gives the value '0', the interviewer must ask him/her why he/she is not prepared to pay to take part in the exercise.*

***2.5-3** "How much would you be prepared to pay to be able to take a ball out of the bag containing an unknown number of white and black balls?"*

The producer can choose one of the following values for 2.5-3:

The producer is not willing to wager any money: 0 FCFA
50 FCFA
100 FCFA
200 FCFA
300 FCFA
400 FCFA
500 FCFA
600 FCFA
700 FCFA
800 FCFA
900 FCFA

1000 FCFA

***2.5-4** If the producer gives the value '0', the interviewer must ask him/her why he/she is not prepared to pay to take part in the exercise.*

→ ***After Question 2.5, the interviewer should provide another voucher of 1 600 FCFA to the producer.***

SECTION 3: PRODUCER'S WILLINGNESS TO PAY FOR ARICA SEED

Now you will have the opportunity to take part in an exercise to understand how you add value to new improved rice varieties.

Willingness to pay for one bag (25g) of ARICA rice seed.
We want to understand how much you would be willing to pay for the opportunity to try a small quantity (25 g) of **seeds** of a new ARICA variety developed by AfricaRice for the ecology "rainfed upland". *The interviewer must show the producer the 25g bag of ARICA rice seed.* This variety has been developed to have good ***drought*** tolerance. It is also characterised by a high yield and a certain resistance to disease. The interviewer should ask question **3A.2**. If the producer says he/she would rather have the money than the 25g **bag** of "ARICA" seed, you must reduce the previous amount by 25 FCFA each time until the farmer chooses "**Seed**". If the producer says he/she prefers to have the seed, you must increase the amount each time by 25 FCFA until the producer chooses "**Money**".
3A.1 Choice of the starting value: this is a random choice. You should select the beginning value in the following list : 13: 600 FCFA ○ 7: 300 FCFA ◉ 6: 250 FCFA ○ 12: 550 FCFA ○ 18: 350 FCFA ○ 18: 850 FCFA ○ 21: 1000 FCFA ○ 1: 25 FCFA ○ 15: 700 FCFA ○ 4: 150 FCFA ○ 2: 50 FCFA ○ 5: 200 FCFA ○ 14: 650 FCFA ○ 10: 450 FCFA ○ 9: 400 FCFA ○ 16: 750 FCFA ○ 17: 300 FCFA ○ 20: 950 FCFA ○ 3: 100 FCFA ○ 19: 900 FCFA ○ 11: 500 FCFA
3A.2 Do you prefer (***amount chosen***) FCFA or the 25g bag of the new ARICA variety (Code : 1= Seed, 2=Money)?
3A.3 Final value chosen by the producer
3A.4 Specify the exact value of the amount the producer is willing to pay for the 25g bag of ARICA seed.

Before carrying out the BDM elicitation of the WTP for ARICA seed, the interviewer must first explain how the BDM elicitation technique works using a bag of fertiliser.

Experiment

Dice games NB: Start first with the small 25g bag of improved rice seed (ARICA 14 & 15), and state: "We are now going to do an exercise in which you can obtain this bag of improved rice variety seed (ARICA) adapted to your ecology.

Explain that the producer can allocate part of the sum of 1600 FCFA that they received (see the values below) in order to receive the seeds. Selection of the amount that corresponds to the amount for which the producer would like to buy the seed. Also, the interviewer must explain that if the producer is going to receive the seeds, that AfricaRice would like to ask the producer to cultivate the ARICA variety during the current season in a small plot (2m x 2m) next to the plot of his/her own variety, and to provide information to AfricaRice on how he/she perceives the qualities of the ARICA variety in relation to the variety he/she is currently growing after harvest.

Stages of the game: (i) The producer selects a value from the numbers of the dice below (2-12) that corresponds to the amount for which he/she would like to buy the seeds; (ii) Then the dice are cast, and if the **value is equal to or below the value selected previously** by the producer, the producer **receives the seeds and has to pay the amount associated with the number of the "dice roll"**; (iii) If however, the value is greater than the value selected previously by the producer, **he/she will not pay anything** and will not receive the improved ARICA rice seed. The producer can also decide that he/she is not willing to wager any money and that he/she is not interested in receiving the seeds.

The producer is not willing to wager any money: 0 FCFA ○
Dice roll= 2 : 100 FCFA ○
Dice roll= 3 : 200 FCFA ○
Dice roll= 4 : 300 FCFA ○
Dice roll= 5 : 400 FCFA ○
Dice roll= 6 : 500 FCFA ○
Dice roll= 7 : 600 FCFA ○
Dice roll= 8 : 800 FCFA ○
Dice roll= 9 : 1000 FCFA ○
Dice roll= 10 : 1200 FCFA ◉
Dice roll= 11 : 1400 FCFA ○
Dice roll= 12 : 1600 FCFA ○

3B.1 Specify the amount chosen by the producer (amount on the dice roll list above)

3B.2 Specify the value of the dice roll associated with the amount chosen by the producer

3B.3 What is the result of the two dice? NB: Add up the numbers on the two dice

3B.4 What is the amount corresponding to the results of the dice (in FCFA)?

3B.5 Will the producer receive the rice seed? (1=Yes ; 0= No)
3B.6 Specify the amount paid by the producer
3B.7 If the producer choses 1600 FCFA as the amount in question 3B.1 (Dice roll= 12 : 1600 FCFA), ask him/her: Hypothetically, how much would you be willing to pay for the seed (if the amount exceeds 1600 FCFA)?

SECTION 4. COMPENSATION FOR SECTION 2 ON THE PREFERENCES REGARDING RISKS

We will now randomly select one of your answers in section 2 to identify your payment.

Payment – Sections 2.1 – 2.3

For this section, the interviewer must use the bag containing 35 numbered balls. Before removing a ball from the bag, he/she must empty the bag and show the ***35 numbered balls*** *to the producer. Once a scenario has been selected, the interviewer must show the producer which variety he/she had previously selected (Variety A or Variety B). He/she must specify that the payment will be 1/100th of the value indicated in* ***questions 2.1 to 2.4.***

He/she must show the producer the bag with 10 balls (emptying the 10 balls from the bag) and specify what the producer's yield would be based on the ball selected. For example, for scenario 1 in series 1, if the producer selected variety A, the interviewer must specify that if the producer selects ***balls numbered 1, 2, or 3****, he/she* ***will receive 400 FCFA****. However, if he/she selects* ***balls 4 to 10****, he/she will only receive 100 FCFA. If the producer had instead chosen variety B1 for this scenario, he/she would have received 680 FCFA if ball number 1 was drawn; or 50 FCFA if one of the balls numbered 2 to 10 was drawn. For series 3, where the odds are 50-50 (every other year), the interviewer can consider that the first scenario occurs if* ***balls numbered 1 to 5*** *are drawn, or the second scenario occurs if* ***balls numbered 6 to 10*** *are drawn.*

The interviewer should randomly select one question from the 35 risk elicitation questions in ***Section 2****. Then ask the producer to draw a ball from a bag, each marked with a number from 1 to 10.* ***Based on this result, give the producer 1/100th of the declared value of the winnings according to his/her choice in Section 2 - or ask for the "lost" money if the question is in Section 2.5 and the producer draws a ball numbered 6 to 10****.*

For example, let's say that question 2.5 to 7 is selected at random and that, for this question, the producer has chosen rice variety B and has taken the ball labeled "2" out of the bag. The interviewer must then give the producer 30 000 FCFA / 100 = 300 FCFA.

Payment – Sections 2.5

We will now play the two scenarios with the balls in the bag.
To begin with, the interviewer must roll a dice to determine whether the bag with 50-50 odds or the 'mystery' bag will be chosen for the exercise. Once the type of bag has been selected in this way, the interviewer must first remind the producer of his willingness to pay (WTP) to take a ball out of the bag (with a chance of winning 1000 FCFA), then have him choose the colour (black or white), and then invite him to take a ball out of the bag.

First, the BDM must be played to determine whether the game will occur based on the producer's willingness to pay; the producer will then be allowed to take a ball out without looking in the bag based on the results of the BDM, at the end of which the appropriate incentives/rewards will be provided to the producer..

4.2-1 Which bag is selected after the roll of the dice – 1-3 = 50-50 bag and 4-6 = mystery bag? (50-50 / mystery bag)

4.2-2 Specify the willingness to pay (WTP) chosen by the producer for the bag selected:

4.2-3 Specify the colour (white or black) and confirm with the producer:

4.2-4 Specify the amount of the dice roll associated with the amount chosen by the producer:

4.2-5 What is the result of the two dice? NB: Add up the numbers on the two dice

4.2-6 What is the amount (in FCFA) corresponding to the results of the dice?

4.2-7 Will the producer take a ball out of the bag? Yes/No

4.2-8 Will the producer receive the 1 000 FCFA?

Total compensation

4.3 What is the total amount received by the producer?

= 2600 FCFA - (result of the BDM) + (result of 4.1) + (result of 4.2)

A5. Histograms of α, σ, λ, and ambiguity aversion