Risk, ambiguity and the adoption of new technologies: experimental evidence from a developing economy

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Abstract

The slow adoption of innovations in less developed countries has long been a puzzle, given the high expected returns. This paper investigates the role of ambiguity-aversion as a fundamental behavioral determinant of technology adoption, motivated by the fact that, almost by definition, farmers have less certain information about the outcomes of new technologies compared with traditional technologies. Using primary data from field experiments used to measure behavioral parameters such as risk and ambiguity aversion, we find that farmers' aversion to ambiguity (but not risk aversion) limits the adoption of new technologies, even when expected profits are quite high. Interventions that reduce uncertainty (in place of interventions that reduce risk) seem a promising way of speeding up the adoption of innovations.

1 Introduction

There is a growing recognition among economists that innovation and the adoption of technological innovations is central to economic growth. [2] In the new growth theory models (for example, **??**), the innovation process involves risky experimentation and learning before adoption, while both innovation and the adoption decision are guided by economic incentives. Given this, there is an obvious interest in understanding how decisions about adoption

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[2] Where innovation is broadly understood to include new products, new processes and new ways of organizing production.

of available technologies are made and, in particular, what may explain their slow adoption.

Much of the empirical work on the microeconomics of adoption, starting with the pioneering study by **?** on the importance of profitability for the adoption of hybrid corn, focused on the adoption of agricultural innovations, reflecting data availability, the flow of innovations (in particular, high-yielding varieties during the Green Revolution) and, in many settings, the importance of the sector in the economy (**?**). Guided by the "poor, but efficient" hypothesis (**?**), much of the analysis emphasized the importance of external constraints, namely market imperfections, in explaining the lack of adoption of such technologies, in detriment of behavioral determinants such as learning or preferences towards time and uncertainty.

In a still classical review of this work, Feder, Just, and Zilberman (1985) include risk preferences and limited access to information as determinants of slow adoption[3], but also stress that a theoretical understanding of the role of risk in the adoption process (building on the expected utility theory (Neumann and Morgenstern, 1944) with the developments introduced by Savage (1954)) was much more developed than the empirical validation of its importance "because [risk] is difficult to measure [hence] most of the empirical work on the role of subjective risk is not yet rigorous enough to allow validation or refutation of available theoretical work" (Feder, Just,

[3]Feder, Just, and Zilberman (1985, p.255) state that "The conventional wisdom is that constraints to the rapid adoption of innovations involve factors such as lack of credit, limited access to information, aversion to risk, inadequate farm size, inadequate incentives associated with farm tenure arrangements, insufficient human capital, absence of equipment to relieve labor shortages (...), chaotic supply of complementary inputs (...) and inappropriate transportation infrastructure".

and Zilberman, 1985, pp.274-275).[4]

In linking risk and learning, Feder, Just, and Zilberman (1985, p.274) suggest that "farmers' technology choices are based on their subjective probabilities and, hence, on their exposure to information regarding new technology" – differences in exposure to information could then explain why some varieties were received more favorably than others. [5] Clearly, in this context, differences in access to information are associated with different "degrees of confidence" in an estimate of probabilities of outcomes or, in other words, with what Ellsberg (1961) defined as ambiguity. [6] Although the original discussion of ambiguity was based on a thought experiment, [7] patterns of

[4]Two other reviews, **?** and Sunding and Zilberman (2001), have a treatment of the importance of risk that is substantially identical to Feder, Just, and Zilberman (1985) suggesting that not much advance has been made in quantifying its empirical importance or in suggesting different theoretical approaches to adoption decisions under uncertainty. Writing almost 20 years later, **?** would explicitly agree with this analysis.

[5]The emphasis on the role of information in adoption motivated a large body of work, both theoretical and empirical, on the role of education (Lin, 1991, Duraisamy, 2002), access to extension (Nkonya, Schroeder, and Norman, 1997) and the role of social learning (Besley and Case, 1993, Foster and Rosenzweig, 1995, Munshi, 2004, **?**). See Feder (1979) for early applications of Bayesian learning in the context of adoption and **?** for a later, more general model, that emphasizes the role of information.

[6]The original definition of ambiguity in this paper is that of "a quality depending on the amount, type, reliability and 'unanimity' of information, and giving rise to one's 'degree of confidence' in an estimate of relative likelihoods" (Ellsberg, 1961, p.657).

[7]In one of the versions of this thought experiment, the two-color urn problem, a decision-maker is presented with a choice of a lottery based on a draw from an urn with a known proportion of lottery balls of two different colors (for example, 25 red balls and 25 black balls) or a lottery based on the draw of a lottery ball from an urn with a known total number of lottery balls (50 balls) but an unknown proportion of either color. The decision-maker would win a certain amount of money if drawing a red ball. Decision-makers who are averse to ambiguity would prefer to bet on the first urn. The rationalization of the preferences that emerged from such experiments is that choosing the first urn is safer than choosing the second because there may actually be zero red balls in the second urn. As noted by (**?**, p.138), in discussing the other decision problem posed by Ellsberg, "While these preferences seem plausible they are inconsistent with subjective expected utility maximization (SEU) . . . The key to Ellsberg's example is the fact that the composition of the urn is incompletely specified; in particular, the relative likelihood of a green as against a blue draw is ambiguous".

behavior similar to the one rationalized in the 'Ellsberg paradox' have been empirically found in a variety of contexts, including economic experiments (?), the market (Sarin and Weber, 1993, Halevy, 2007, Capon, 2009) and subsistence farmers in developing countries (Akay et al., 2009). [8] However, the potential importance of preferences towards ambiguity has been largely ignored in the adoption literature despite the fact that the probability distribution of outcomes associated with a new technology is rarely known (Liu, 2008) and thereby provides a natural setting to test the importance of such preferences. [9]

In this paper, we address the importance of ambiguity in explaining the adoption of a new crop, non-glutinous rice, in the context of a developing country, Lao PDR, which is simultaneously very poor and experiencing fast growth. We describe this new technology, its context and the data we collected regarding its adoption in section 2. We used behavioral field experiments to elicit farmers' risk and ambiguity preferences, together with a more traditional household survey that addresses many of the adoption determinants studied in the early literature. Contrary to others, we find that risk and ambiguity preferences are not correlated and, in section 3, we show that ambiguity, but not risk, matter for the adoption decision. We conclude in section 4 with a discussion of the policy implications of these findings.

[8] Theoretically, ambiguity could have effects such as increasing savings in the presence of uncertainty, or providing an incentive for hedging in portfolio choice problems (??). The implications of models of ambiguity-aversion are generally more cautious decision-making under ambiguity and more complicated procedures for updating expectations compared with the Bayesian model (?).

[9] The exceptions, discussed below, are Engle-Warnick, Escobal, and Laszlo (2007) and Alpizar, Carlsson, and Naranjo (2009).

2 Non-glutinous rice in Laos: context and data

Lao PDR is a very poor country in SE Asia, heavily dependent on the agricultural sector which accounts for nearly half of its GDP and employs 77% of its labour force (Bountavy and Myers, 2006). Simultaneously, poverty remains a rural phenomenon, with 87% of the country's poor living in farmer-headed households (NSC, 1999).

Despite the introduction in 1986 of the New Economic Mechanism (NEC) with the objective of liberalizing the economy and broadening the nation's exposure to international markets, the largest proportion of the country's agricultural output remains focused on glutinous-rice farming: rice, mostly produced on small family farms, dominates the agricultural sector, accounting for 50% of agricultural output of which 85% is glutinous rice (Schiller, 2006). Taking these different values together, glutinous rice represents roughly 20% of the country's GDP.

For the purposes of the present study, glutinous rice is the "existing" technology, to be compared with the introduction of non-glutinous rice as a "new" technology. Unlike glutinous rice, which is typically grown for direct consumption, non-glutinous varieties are cultivated as a base ingredient in the production of noodles and beer. Widely produced in neighboring Thailand and Vietnam, these varieties[10] offer farmers greater yields, shorter growth maturity and higher, more stable prices (SNV, 2009).

This new crop has been promoted in Central Laos by the Dutch Development Agency (SNV), in collaboration with local mills. Farmers adopting

[10] We focus on the two varieties most commonly adopted in the region, specifically the varieties VND 95-20 and CR203.

the crop enter a contract with a mill, who agrees to purchase a specified amount of paddy rice that meets predefined quality standards (most important, moisture level) at a pre-specified price and time, while also providing production inputs and credit.

The price paid in 2010 was considerably higher than the price that farmers may receive for glutinous rice and the additional revenue seems to translate into additional profits, as the two crops require similar amounts of input. A back-of-the-envelope calculation suggests that *additional* profits are of the order of US$200 per hectare (roughly 25% of the value of income per capita in that year). Although there is certainly an element of trust underlying these contracts [11] the crop also seems to be less risky, at least with respect to market conditions given the guaranteed prices. Even so, adoption of the new crop variety has been slow, as admitted by those responsible for the program.

In order to understand the reasons underlying the slow adoption of non-glutinous rice, we conducted a household survey and behavioral field experiments in one village (Natai) in the province of Khammouane, Lao PDR, during July 2010. The village was chosen with SNV's assistance because it was considered to be representative of the adoption behavior in the region. Whilst non-glutinous rice was introduced to this region during the 2009 dry season it has so far only been partially adopted, providing an ideal case study for examining the factors that affect the adoption decision. [12]

[11] Millers may be personally unknown to farmers so the possibility that contracts may not be honored exists, although the issue was never raised by the farmers interviewed.

[12] The size of Natai also meant that it was possible to interview 66 of the total number of 69 household heads for this study.

Household heads were interviewed prior to the field experiments and, in addition to information on household demographic and socioeconomic characteristics, land use and crops produced in the last two seasons, we also collected detailed information on the cultivation of glutinous and non-glutinous rice varieties, including yield, price received, capital equipment, labor and exposure to shocks. Table 1 presents some summary statistics for the key variables of interest from the household survey.

Table 1: Summary statistics

Variable	N	Mean	Std. Dev.	Min.	Max.
White rice	66	0.363	0.244	0	1
Glutinous rice	66	0.556	0.272	0	1
Gender (household head)	66	1.136	0.346	1	2
Age (household head)	66	48.015	10.845	22	76
Education (household head)	66	5.197	3.024	0	15
Household size (no. members)	66	4.136	1.311	2	8
Land (ha)	66	2.426	1.501	0.7	9
Extension (visits from officer)	66	2.197	0.845	0	4

The average interviewee in the sample was 48 years old and had completed 5.2 years of education. Nearly all farmers had received support from an extension service, with an average of around 2 visits from extension services. Glutinous rice was the predominant crop cultivated in Natai village, with an average of 1.27 hectares per household. Non-glutinous varieties were grown on an average of 0.92 hectares per household, with 54 (82%) of the households growing some area of the crop, although nearly all of them have relatively limited experience with non-glutinous relative to glutinous rice.

All survey respondents participated in decision-making experiments designed to measure risk and ambiguity preferences. Given relatively low levels of formal education in Natai, the experiments were implemented with the help of visual aids to assist the respondents in developing a clear understanding of the probabilities of the alternative payoffs. Participants in the experiments were paid for their participation and, depending on outcomes, could receive up to 40,000 Lao Kip (LAK)[13], an amount that is higher than the average daily household income in the district and close to 2 days of rural wage. Given that these experiments are still infrequently used we proceed by describing in more detail the procedure used in the elicitation of risk preferences and ambiguity.

2.1 Eliciting risk preferences

Most of the risk elicitation procedures follow the pioneer work of Binswanger (1980) or Holt and Laury (2002). The Holt and Laury (2002) procedures use choices from a list of binary lotteries that differ in expected payoffs and variance to infer parameters for risk-aversion from the choices made.

Our instrument, presented in Table 2, is slightly different as we ask respondents to compare certain amounts and lotteries, in order to more directly elicit certainty equivalents for the lotteries, that is, the certain amount that is equally preferred to a risky alternative. [14] Participants were offered 11 choices between a certain payoff (option one) and the risky prospect (option two), with the certain payoff increasing in 2000 LAK increments from 0 to 20000 LAK and were informed they would receive real payment that would depend on the choices they made for each of the 11 options. [15]

[13]At the time of the experiment, the exchange rate was LAK 8,000=US $1.00

[14]This approach is similar to the one used by Akay et al. (2009) and Capon (2009).

[15]To be more concrete, participants would draw a ticket, numbered from 1 to 11, and

Table 2: Certainty Equivalent Procedure

Turn	Option one: Certain Payments	Option two Urn/coin toss	Switchpoint from 1 to 2	CE at switchpoint	Frequency	
					Urn	Coin toss
1	0	0.5 (0), 0.5 (20,000)	–	0		
2	2,000	0.5 (0), 0.5 (20,000)	1 to 2	1,000	2	1
3	4,000	0.5 (0), 0.5 (20,000)	2 to 3	3,000	3	6
4	6,000	0.5 (0), 0.5 (20,000)	3 to 4	5,000	3	8
5	8,000	0.5 (0), 0.5 (20,000)	4 to 5	7,000	8	8
6	10,000	0.5 (0), 0.5 (20,000)	5 to 6	9,000	8	8
7	12,000	0.5 (0), 0.5 (20,000)	6 to 7	11,000	13	11
8	14,000	0.5 (0), 0.5 (20,000)	7 to 8	13,000	7	10
9	16,000	0.5 (0), 0.5 (20,000)	8 to 9	15,000	19	10
10	18,000	0.5 (0), 0.5 (20,000)	9 to 10	17,000	2	4
11	20,000	0.5 (0), 0.5 (20,000)	10 to 11	19,000	1	0

For the first value of the certain payments (0 LAK) participants would prefer to play the risky prospect. As the certain payments get larger, most participants would prefer the certain payoff and, given this, at some point they will reveal their preferences towards risk by switching from option 2 to option 1. [16] We calculate the certainty equivalent as the midpoint between the lowest certain payment for which the participant chooses option 1 and the highest certain payment for which they choose option 2 (Eggert and Lokina, 2007). The elicitation of this value will then allow us to compute the risk premium (that is, the amount that the respondent is willing to pay in order to avoid risk) in the usual way, as the difference between the expected value and the certainty equivalent. Knowledge of the risk premium allows

would play the prospect corresponding to their selection for the respective choice. One was selected at random for payment, with the participant either receiving a certain payment or playing the prospect depending on the specific choice made when facing the selected option. See the discussion of this procedure in, for example, (**?**).

[16] All participants switched from option 2 to option 1 only once.

for inference regarding a decision maker's attitude towards risk: a positive (negative) risk premium implies risk aversion (risk seeking) behavior while no risk premium implies that the subject is indifferent to risk.

For each participant, certainty equivalents were elicited using two different risky prospects, a coin toss and an urn. The coin toss offered the participant equal probabilities of winning 20,000 LAK and nothing. The urn, containing exactly 5 red and 5 yellow balls, offered the participant the possibility of winning 20,000 LAK if a red ball was drawn and nothing for a yellow ball. Although both have the same probability distributions and payoffs, the use of different mechanisms allows us to account for potential bias towards a particular way of eliciting preferences, leading to a more balanced assessment of risk preference.

The distribution of the outcomes for both procedures is presented in the last two columns of Table 2. The results suggest that the majority of the participants were risk-preferring, with small differences between the two procedures in terms of the number of participants that behaved as risk-preferring (63.3% and 52.7%, for the urn and coin toss respectively) and an identical median value for the elicited certainty equivalent of LAK 11000. [17]

In addition to these games, we asked participants about how they feel about risks as suggested, for example, by **?**. Participants were visually presented with a numbered scale ranged from 1 to 10, where 1 represented the statement "I never like to take risks" and 10 represented "I always like to

[17] The mean certainty equivalent suggests that participants were more risk-preferring for the urn prospect than coin toss, as the urn prospect displayed average certainty equivalent of LAK 11000 compared to a marginally risk-averse certainty equivalent of roughly LAK 9900 for the coin toss.

take risks", and asked to rank themselves in that scale.[18] The majority (66.6%) of the participants provided values between 6 and 10, with an average score of 6.48 (and standard deviation of 2.13). The distribution of these results (not shown) is similar to the one obtained with the two games played by the participants, already described, suggesting that most participants are willing to take risks and think of themselves as often willing to take risks.

This data then allows us to address a first methodological question: does the way risk preferences are measured matter for how we classify respondents' behavior? To address this question, we estimate the correlation between the relative rankings of participants' results for each measurement using Spearman correlation coefficients. [19] The results are presented in Table 3, where values in bold are statistically significant at the 5% level. The correlations between all risk measurements are statistically significant and relatively high: the positive correlation between the coin toss and urn prospects (0.5107, $p < 0.01$) largely suggests that the different procedures lead to similar conclusions. Similarly, both prospects for the certainty equivalent procedure are also statistically correlated with the self-assessed risk preference measure. Summarizing these results, all three approaches, including the relatively simpler to implement "self-assessment scale", seem to offer similar conclusions regarding participants attitudes towards risk.

[18]Eliciting individual attitudes to risk using a singular self-assessment question has been frequently used as a proxy for risk aversion. See, for example, Kastens and Featherstone (1996), Patrick and Ullerich (1996), Bard and Barry (2000).

[19]Pearson correlation coefficients cannot be used given the ordinal nature of the third measure of risk preferences.

Table 3: Correlation between risk and ambiguity measures

	Risk: Coin toss	Risk: Urn	Risk: Self-assessed	Ambiguity
Risk: coin toss	1			
Risk: urn	**0.511** (0.00)	1		
Risk: self-assessed	**0.247** (0.045)	**0.282** (0.022)	1	
Ambiguity	0.216 (0.082)	0.097 (0.440)	-0.032 (0.798)	1

2.2 Eliciting ambiguity preferences

Numerous empirical studies of ambiguity have tested Ellsberg (1961) thought experiment, mostly in laboratory settings in developed countries (for example, Becker and Brownson, 1964, MacCrimmon and Larsson, 1979, Bowen and Zi-lei, 1994), with the number of field experiments measuring ambiguity preferences in developing countries being much smaller (Engle-Warnick, Escobal, and Laszlo, 2007, Alpizar, Carlsson, and Naranjo, 2009, Akay et al., 2009).

Our instrument to measure ambiguity preference is represented in Table 4 and is a variation of Ellsberg's 3-color urn experiment, similar to that used by Lauriola and Levin (2001) and Capon (2009) in a laboratory setting. It involves a choice set between an unambiguous urn (option one) and an ambiguous urn (option two), manipulating the objective probability of success in the unambiguous urn whilst leaving the ambiguous urn unchanged. Participants were presented with a set of 11 choices, where each choice asked them to select between playing the unambiguous urn or the ambiguous one. In each choice, the unambiguous urn held a known proportion of ten colored balls, with the proportion of yellow balls (and hence the probability of winning) decreasing in increments of one ball for each successive choice. This

Table 4: Ambiguity Preferences: Ellsberg Urns

Turn	Option one: Urn	Expected Monetary Value (EMV)	Option two	EMV at Switchpoint	Frequency
1	1 (20,000)	20,000	? , ?	20,000	
2	0.1 (0), 0.9 (20,000)	18,000	? , ?	19,000	4
3	0.2 (0), 0.8 (20,000)	16,000	? , ?	17,000	4
4	0.3 (0), 0.7 (20,000)	14,000	? , ?	15,000	8
5	0.4 (0), 0.6 (20,000)	12,000	? , ?	13,000	10
6	0.5 (0), 0.5 (20,000)	10,000	? , ?	11,000	9
7	0.4 (0), 0.6 (20,000)	8,000	? , ?	9,000	13
8	0.3 (0), 0.7 (20,000)	6,000	? , ?	7,000	10
9	0.2 (0), 0.8 (20,000)	4,000	? , ?	5,000	5
10	0.1 (0), 0.9 (20,000)	2,000	? , ?	3,000	3
11	1 (0)	0	? , ?	1,000	0

was reinforced visually, where for each choice the participant was shown one yellow ball removed from the urn and replaced by a red ball. Participants were advised the ambiguous urn contained 10 balls, although the number of each type of balls was not revealed. Prior to the experiment, participants were informed that payment would be determined in the same way as for the risk preference experiments, with yellow and red balls rewarded them with LAK 20,000 and nothing, respectively.

Several factors made this approach appealing in the field. In particular, the unknown and known probability distributions could be visually represented to the participants, permitting a clearer understanding of the decision. This was reinforced by the fact that the binary choice list, payoffs and payment determination closely resembled the procedures used to elicit risk preferences, allowing the participants to understand the procedure through prior experience.

One can value ambiguity preferences as the objective probability of winning the unambiguous urn prior to crossing over to the ambiguous urn (as, for example, Lauriola and Levin (2001) and Capon (2009) do), after setting a normative anchor at a predetermined probability value as defining ambiguity neutrality. As Lauriola and Levin (2001), we set that anchor as being $p = 0.5$. To illustrate, and using the values presented in Table 4, a participant who crosses from the unambiguous urn over to the ambiguous one on the third choice prefers the unknown ambiguous prospect rather than the objective $p = 0.8$ of the unambiguous prospect. In a way analogous to the risk experiments, we can define an equivalent monetary value associated with neutrality towards ambiguity. In the case of this experiment, ambiguity neutrality is associated with an equivalent monetary value of LAK 10,000 with ambiguity preferring (averse) participants displaying an equivalent monetary value greater (smaller) than LAK 10,000. In the example just given, the midpoint-calculated equivalent monetary value of LAK 17,000 reveals that such a participant (who chooses the ambiguous prospect instead of an unambiguous one with an objective probability of winning of 80%) would be classified as ambiguity-preferring while, for example, crossing over at the eighth choice (with an equivalent monetary value of LAK 7,000) would imply they are averse to ambiguity.

The last column of Table 4 presents the results of the probability equivalence procedure measuring ambiguity preferences. The distribution of results is evenly spread and suggests the ambiguity attitudes for farmers in Natai were fairly heterogeneous, with slight skewness towards ambiguity-preference (53% of participants elicited equivalent monetary values of more than LAK 10,000). Comparing these results to earlier papers using similar samples (Akay et al., 2009) and procedures (Lauriola and Levin, 2001), the participants in our experiment appear to be more ambiguity-preferring.

One important question, unsolved in the literature, is whether ambiguity and risk preferences are so similar as to defy a useful distinction. As previously, we use Spearman rank correlations (this time between our measure of preferences towards ambiguity and the different measures of preferences towards risk) to address this question. The results are presented in the bottom row of table 3 and, contrary to previous work, we find that ambiguity measures exhibit no statistical correlation with the risk measures at the usual 5% level of significance and only in one of the cases, the coin-toss certainty equivalent procedure, does it exhibit a correlation that is significant at the 10% level. In our data, at least, ambiguity preferences seem distinct from risk preferences and, as such, can provide additional information regarding the determinants of particular decisions, namely adoption, to which we now turn.

3 Explaining adoption decisions

The primary question of this paper is to understand whether there is a separate role for behavioral preferences and, in particular, ambiguity preferences, in explaining the adoption of innovations, using the slow adoption of non-glutinous rice as a case study. Because most of the households in the village where we conducted our study have already adopted non-glutinous rice, we study their decision in terms of intensity of adoption by specifying a model of the form:

$$Y^{\star} = X_i\beta + \varepsilon_i \tag{1}$$

where $Y_i^{\star}$ is the unobserved latent dependent variable that represents the proportion of non-glutinous rice planted by farmer i, X_i is the set of observed explanatory variables expected to influence adoption by farmer i, β is a vector of parameters to be estimated and ε_i is a random error term. The observed proportion on non-glutinous rice grown by farmers, y_i, is left censored at 0 (no adoption) if the unobserved latent variable $Y_i^{\star}$ does not exceed the threshold level 0, after which it becomes a continuous function of the explanatory variables, being potentially right censored at 1 for those farmers that devote all their land to this new technology.

$$y_i = \begin{cases} Y_i^{\star} & \text{if } Y_i^{\star} \geq 0 \\ 0 & \text{if } Y_i^{\star} < 0 \end{cases} \tag{2}$$

Under the additional assumption that $\varepsilon_i \sim N(0, \sigma^2)$, we can estimate this relation as a Tobit model (Tobin, 1958), an approach used previously in studies of agricultural technology adoption, including studies of conservation adoption (Norris and Batie, 1987, Gould, Saupe, and Klemme, 1989) and the adoption of alternative crop varieties (Adesina and Zinnah, 1993).

The explanatory variables include, in addition to risk and ambiguity preferences, several other correlates of adoption identified in the literature[20] and for which we have information, collected through the household survey

[20] See, for example, Binswanger (1978), Akinola (1987), Polson and Spencer (1991), Nkonya, Schroeder, and Norman (1997), Bultena and Hoiberg (1983), Gould, Saupe, and Klemme (1989), Duraisamy (2002), Liu (2008).

that we conducted: farm size, visits from extension services, age and years of education. [21]

There are two concerns with our data. The first is that we only have cross-sectional data collected after the adoption decision. Previous studies (for example, Besley and Case, 1993) raised the concern that any ex-post measurement of explanatory variables could be affected by the adoption decision, therefore being endogenous. Our selected covariates are unlikely to suffer from this problem as they are unchanging over time, and as such unlikely to be affected by initial adoption decisions that date as late as the 2009 dry season. The second is that, given the correlation between the different measures of risk preferences, multicollinearity may be a problem. To circumvent it, we will estimate a separate Tobit model with each of the risk preference variables included separately.

Our estimates are presented in table 5. [22] Although we are mostly interested in the relative importance of risk and ambiguity, it is important to notice that the sign of all other covariates are as expected, given the results in the ex ante literature. However, the estimates are not precisely estimated at the usual levels of significance of 5%. Focusing on our central question, the importance of behavioral preferences, an immediate first conclusion is that ambiguity preferences matter in explaining adoption, but risk preferences, irrespective of the specific measurement procedure, do not.

As it is known, the Tobit estimates cannot be directly interpreted given

[21]Some summary statistics were presented in Table 1.

[22]We only present the results when including all risk measurements. There are no meaningful differences between these estimates and those obtained when we separately include each of the risk measures. The results of the other models are available upon request.

Table 5: Estimation results : tobit

Variable	Coefficient (Std. Err.)
Gender (household head)	-0.007
	(0.095)
Age (household head)	0.000
	(0.003)
Education (household head)	0.006
	(0.011)
Household size	-0.008
	(0.028)
Extension visits	0.129**
	(0.041)
Land	0.046†
	(0.025)
Risk: coin toss	0.013
	(0.009)
Risk: urn	-0.008
	(0.009)
Risk: self-assessed	0.000
	(0.016)
Ambiguity	0.026**
	(0.008)
Intercept	-0.387
	(0.283)
σ	0.237**
	(0.024)
N	66
Log-likelihood	-11.593
Pseudo R62	0.587

Significance levels : † : 10% $*$: 5% $**$: 1%

that, although they allow us to observe both the significance and direction of the relationship between the dependent and explanatory variables, the coefficients represent the marginal effects of changes on the unobserved latent variable [23]. In order to understand whether ambiguity also matters in an economic sense, we follow the Tobit decomposition framework suggested in McDonald and Moffit (1980) to obtain the marginal effects of the explanatory variables on the adoption probability and use intensity. [24]

The results of this decomposition are shown in table 6, distinguishing between the marginal effects of changes on the probability and intensity of adoption. Visits from extension services show the strongest significant relationship to the adoption of non-glutinous rice, with an additional visit

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[23] That is $\beta = \frac{\partial E(Y_i^{\star})}{\partial X_i}$

[24] If we let the expected value of the dependent variable across all observations be represented by $E(y_i)$, the expected value of the dependent variable conditional of a farmer growing non-glutinous rice be given as $E(y_i|y_i > 0)$ and the probability of the farmer being uncensored (i.e. the probability of adoption) be represented by $F(z)$, the cumulative normal distribution of z where $z = \frac{(X_i\beta)}{\sigma}$. The relationship between these variables can be shown as:

$$E(y_i) = F(z)E(y_i|y_i > 0) \tag{3}$$

Differentiating equation (3), the marginal effects of a change in variable X_i on $E(y_i)$ is expressed as:

$$\frac{\partial E(y_i)}{\partial X_i} = F(z)\frac{\partial E(y_i|y_i > 0)}{\partial X_i} + E(y_i|y_i > 0)\frac{\partial F(z)}{\partial X_i} \tag{4}$$

Equation (4) reveals that the marginal change in the observed dependant variable y_i can be decomposed into our two parts of interest, represented in equations (5) and (6). The marginal effect of variable X_i on the conditional expected value $E(y_i|y_i > 0)$, which we can interpret as the change in adoption intensity, is:

$$\frac{\partial E(y_i|y_i > 0)}{\partial X_i} = \beta_i(1 - \frac{zf(z)}{F(z)} - \frac{f(z)^2}{F(z)^2}) \tag{5}$$

where $f(z)$ represents the standard normal density and β_i represents the vector of Tobit estimates for variables X_i. The change in the probability of adoption as variable X_i changes is:

$$\frac{\partial F(z)}{\partial X_i} = f(z)\frac{\beta_i}{\sigma} \tag{6}$$

increasing the probability of adoption by 7.2% and the expected intensity by 9.8%. Although this is consistent with the findings of other authors [25] care must be taken in interpreting this result due to possibility of reverse causality, that is, the possibility that the number of extension visits increased when non-glutinous adoption increased. Farm size significantly and positively influenced adoption. A farmer with one extra hectare of land is 2.4% more likely to adopt non-glutinous rice and, when adopting, will grow 3.3% more of the new variety. The variables age, household size, education and gender did not significantly influence the adoption decision.

Table 6: MacDonald and Moffitt decomposition of Tobit estimates

	Adoption probability		Intensity	
Variable	Coef.	Std. Err.	Coef.	Std. Err.
Gender (household head)	0.003	0.053	0.004	0.071
Age (household head)	-0.000	0.002	-0.000	0.002
Education (household head)	0.003	0.006	0.004	0.009
Household size	-0.004	0.016	-0.006	0.021
Extension visits	0.073**	0.029	0.100**	0.031
Land	0.025†	0.015	0.035†	0.019
Risk: coin toss	0.007	0.010	0.009	0.010
Risk: urn	-0.005	0.010	-0.007	0.010
Risk: self-assessed	0.001	0.008	0.000	0.011
Ambiguity	0.0145**	0.000	0.020 **	0.000

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

The estimates suggest participants who were more averse to ambiguity had a greater likelihood of either adopting less non-glutinous rice on their land or not adopting it at all. A farmer who has an equivalent monetary value of LAK 5000 less than another farmer (i.e. they were more ambiguity-averse) subsequently has a 7.3% lower expected probability of adopting the

[25] For example, Nkonya, Schroeder, and Norman (1997).

new variety and is expected to grow 10% less of the new variety on their plots if they have decided to adopt. Our finding extends beyond the results of previous attempts to measure the importance of ambiguity (Engle-Warnick, Escobal, and Laszlo, 2007, Alpizar, Carlsson, and Naranjo, 2009) by demonstrating that the probability and intensity of technology adoption decreases with ambiguity-aversion.

On the other hand, and contrary to the long-held notion that risk-aversion prevents the adoption of new technology (Feder, 1980, Just and Zilberman, 1983, Knight, Weir, and Woldehanna, 2003, Liu, 2008), risk preferences appear to have no significant relationship with adoption decisions. Given there is low or no correlation between our measures of risk and ambiguity preferences, our results suggest that the decision making process under ambiguity is different from the decision-making process under risk.

4 Conclusions

Given the importance of innovation, the incomplete adoption of new technologies has appropriately received much attention in economics. In addition to a number of market constraints, risk-aversion dominates the discussion on the behavioral determinants of this decision. Somewhat paradoxically, given that the outcomes of innovations are unknown to adopters (or at least early adopters), not much attention has been paid to preferences towards scenarios characterized by unknown probabilities that Ellsberg (1961) called ambiguity.

In this paper we addressed the question of whether a farmer's aversion to ambiguity is important in explaining adoption decisions. To answer this, a unique dataset was collected, combining field experiments intended to measure the behavioral parameters of risk and ambiguity preferences with a household survey, collecting information on the technology choices and socioeconomic characteristics of farmers in one developing country. Given the way we measure innovation, we are able to extend beyond previous work, in quantifying both the decision to adopt and the intensity of adoption and to avoid the problems with the definition of innovation that limit earlier studies. [26]

We present two main conclusions. First, farmers in our sample have distinct preferences towards risk and ambiguity. Second, and perhaps more importantly, we find that ambiguity-aversion, but not risk-aversion, significantly reduces both the probability and intensity of adoption. These findings are important for two reasons.

Firstly, these findings have potential policy implications. The vast majority of the literature that proposes risk-aversion as a possible explanation for hindered adoption in developing countries goes on to suggest that crop insurance (Liu, 2008) and money-back guarantees (Sunding and Zilberman, 2001) are means to potentially hedge against production risk and reduce the fear of loss associated with new technology. Our finding that ambiguity, not risk, is important in explaining adoption decisions, implies that policy should be directed at ensuring farmers have access to more information about the performance of new innovations, allowing them to make more accurate subjective probability evaluations on new innovations. Our additional finding,

[26] For example, Engle-Warnick, Escobal, and Laszlo (2007).

that adoption responds positively to extension, reinforces this conclusion.

Finally, this study connects the findings of field experiments to tangible decisions in the real world. The external validity of game experiments has been the subject of long standing debate (Samuelson, 2005). Unlike experiments conducted in laboratory environments which hypothesise how risk and ambiguity dictate decision-making, our subjects are the decision-makers. The results of this study suggest that game experiments can predict real decisions, hence strengthening their validity.

Our experimental procedures elicited participants' risk and ambiguity preferences across the domain of gains. Further comprehension of the importance of risk and ambiguity on a farmers adoption decisions could be achieved by measuring preferences over gains and losses. Prospect theory (Kahneman and Tversky, 1979) describes a "reflection effect" where a decision-maker exhibits risk-aversion in the domain of gains and is relatively risk-seeking in the domain of losses, perhaps more accurately predicting the behavior of inexperienced individuals (List, 2003). [27] There lies potential for future research to identify whether this exists among farmers in the developing world and what bearing it has on their preferences to risk, ambiguity and adoption.

References

Adesina, A., and M. Zinnah. 1993. "Technology characteristics, farmer perceptions and adoption decisions: a Tobit model application in Sierra

[27] This reflection effect has also been observed under ambiguity, with differing attitudes over gains and losses by Chakravarty and Roy (2009).

Leone." *Agricultural Economics* 9:297–311.

Akay, A., P. Martinsson, H. Medhin, and S. Trautmann. 2009. "Attitudes Toward Uncertainty Among the Poor: Evidence from Rural Ethiopia." Unpublished, IZA Discussion Paper No. 4225.

Akinola, A. 1987. "An application of Peobit analysis to the adoption of tractor hiring service scheme in Nigeria." *Oxford Development Studies* 16:70–82.

Alpizar, F., F. Carlsson, and M. Naranjo. 2009. "The effect of risk, ambiguity, and coordination on farmers' adaptation to climate change: A framed field experiment." Unpublished, rapport nr.: Working Papers in Economics 382.

Bard, S., and P. Barry. 2000. "Developing a scale for assessing risk attitudes of agricultural decision makers." *Management Review* 3:9–25.

Becker, S., and F. Brownson. 1964. "What price ambiguity? On the role of ambiguity on decision-making." *Journal of Political Economy* 72:65–73.

Besley, T., and A. Case. 1993. "Modeling technology adoption in developing countries." *The American Economic Review* 83:396–402.

Binswanger, H. 1980. "Attitudes toward risk: experimental measurement in rural India." *American Journal of Agricultural Economics* 62:395.

—. 1978. *The economics of tractors in South Asia: An analytical review*. Agricultural Development Council.

Bountavy, S., and C.N. Myers. 2006. "International trade and human development : Lao PDR 2006 : the third Lao PDR national human development report." Unpublished, Committee for Planning and Investment, National Statistics Centre : United Nations Development Programme, Vientiane.

Bowen, J., and Q. Zi-lei. 1994. "Robust Tolerance for Ambiguity." *Organizational behavior and human decision processes* 57:155.

Bultena, G., and E. Hoiberg. 1983. "Factors affecting farmers' adoption of conservation tillage." *Journal of Soil and Water Conservation* 38:281.

Capon, T. 2009. "An experimental study of risk, ambiguity and market behaviour." Unpublished, PhD dissertation Griffith University.

Chakravarty, S., and J. Roy. 2009. "Recursive expected utility and the separation of attitudes towards risk and ambiguity: an experimental study." *Theory and Decision* 66:199.

Duraisamy, P. 2002. "Changes in returns to education in India, 1983-94: by gender, age-cohort and location." *Economics of Education Review* 21:609.

Eggert, H., and R. Lokina. 2007. "Small-scale fishermen and risk preferences." *Marine Resource Economics* 22:49.

Ellsberg, D. 1961. "Risk, Ambiguity and the Savage axioms." *Quarterly Journal of Economics* 75:643.

Engle-Warnick, J., J. Escobal, and S. Laszlo. 2007. "Ambiguity aversion as a predictor of technology choice: Experimental evidence from Peru." Unpublished, CIRANO Working Papers.

Feder, G. 1980. "Farm Size, Risk Aversion and the Adoption of New Technology under Uncertainty." *Oxford Economic Papers* 32:263.

—. 1979. "Pesticides, information, and pest management under uncertainty." *American Journal of Agricultural Economics* 61:97.

Feder, G., R. Just, and D. Zilberman. 1985. "Adoption of agricultural innovations in developing countries: a survey." *Economic Development and Cultural Change* 33:255.

Foster, A., and M. Rosenzweig. 1995. "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture." *Journal of Political Economy* 103:1176.

Gould, B., W. Saupe, and R. Klemme. 1989. "Conservation tillage: the role of farm and operator characteristics and the perception of soil erosion." *Land Economics* 65:167.

Halevy, Y. 2007. "Ellsberg revisited: An experimental study." *Econometrica* 75:503.

Holt, C., and S. Laury. 2002. "Risk aversion and incentive effects." *American economic review* 92:1644–1655.

Just, R., and D. Zilberman. 1983. "Stochastic Structure, Farm Size, and Technology Adoption in Developing Agriculture." *Oxford Economic Papers* 35:307–328.

Kahneman, D., and A. Tversky. 1979. "Prospect Theory: An Analysis of Choice Under Risk." *Econometrica* 47:263–291.

Kastens, T., and A. Featherstone. 1996. "Feedforward backpropagation neural networks in prediction of farmer risk preferences." *American Journal of Agricultural Economics* 78:400–415.

Knight, J., S. Weir, and T. Woldehanna. 2003. "The role of education in facilitating risk-taking and innovation in agriculture." *Journal of Development Studies* 39:1–22.

Lauriola, M., and I. Levin. 2001. "Relating individual differences in attitude toward ambiguity to risky choices." *Journal of Behavioral Decision Making* 14:107–122.

Lin, J. 1991. "Education and innovation adoption in agriculture: evidence from hybrid rice in China." *American Journal of Agricultural Economics* 73:713–723.

List, J. 2003. "Does Market Experience Eliminate Market Anomalies?" *Quarterly Journal of Economics* 118:41–71.

Liu, E. 2008. "Time to change what to sow: risk preferences and technology adoption decisions of cotton farmers in China." Unpublished, PhD dissertation, Princeton University.

MacCrimmon, K., and S. Larsson. 1979. "Utility Theory: Axioms Versus."

McDonald, J., and R. Moffit. 1980. "The use of Tobit analysis." *Review of Economics and Statistics* 62:318–321.

Munshi, K. 2004. "Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution." *Journal of Development Economics* 73:185–213.

Neumann, J.V., and O. Morgenstern. 1944. *The Theory of Games and Economic Behaviour*. Princeton: NJ.: Princeton University Press.

Nkonya, E., T. Schroeder, and D. Norman. 1997. "Factors affecting adoption of improved maize seed and fertiliser in northern Tanzania." *Journal of Agricultural Economics* 48:1–12.

Norris, P., and S. Batie. 1987. "Virginia farmers' soil conservation decisions: An application of Tobit analysis." *Southern Journal of Agricultural Economics* 19:79–90.

NSC. 1999. "The Household of Lao PDR: Social and Economic Indicators, Lao Expenditure and Consumption Survey 1997/1998, LECS 2." Unpublished, NSC (National Statistics Centre)State Planning Committee, Vientiane.

Patrick, G., and S. Ullerich. 1996. "Information sources and risk attitudes of large-scale farmers, farm managers, and agricultural bankers." *Agribusiness* 12:461–471.

Polson, R., and D. Spencer. 1991. "The technology adoption process in subsistence agriculture: The case of cassava in Southwestern Nigeria." *Agricultural Systems* 36:65–78.

Samuelson, L. 2005. "Economic theory and experimental economics." *Journal of Economic Literature* 43:65–107.

Sarin, R., and M. Weber. 1993. "Effects of ambiguity in market experiments." *Management Science* 39:602–615.

Savage, L. 1954. *The Foundations of Statistics*. New York: Wiley.

Schiller, J. 2006. *Rice in Laos*. Los Banos, Philippines: International Rice Research Institute.

SNV. 2009. *Baseline Survey to Identify cash crops for VCD in Nongbok District*. Thakhek: SNV (Netherlands Development Organisation).

Sunding, D., and D. Zilberman. 2001. "Chapter 4 The agricultural innovation process: Research and technology adoption in a changing agricultural sector." In L. Bruce and C. Gordon, eds. *Handbook of Agricultural Economics*. 207-261: Elsevier.

Tobin, J. 1958. "Estimation of Relationship for Limited Dependant Variables." *Econometrica* 26:26–36.