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Daichi Shimamoto[†‡], Hiroyuki Yamada[§], and Ayako Wakano[††]

Abstract

This paper investigates how farmers' risk attitudes affected the adoption of agricultural technology in a rural area in Cambodia. We incorporated prospect theory to farmers' utility function and examined the effect of the risk attitude of farmers to the adoption of two technologies: adoption of a moisture meter for measuring the moisture content of seeds, a recently introduced post-harvest technology, and a modern rice variety that was introduced in the 1990s. The results indicated that farmers overweighted a small probability and risk averse farmers adopted a moisture meter to measure the moisture contents of seeds significantly. With respect to the modern rice variety, farmers' risk attitude did not affect the adoption. Our results and the results of a previous study imply that the type of risk and uncertainty faced by farmers at the time of decision-making of its adoption partly determine the effect of risk attitude on agricultural adoption.

JEL classification code: O14, O33

Keywords: technology adoption, risk preferences, prospect theory

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1. Introduction

One of the important roles of agricultural extension services and international aid agencies in rural development is to make more efficient production technologies available to local farmers through diffusion and adoption assistance. Despite the advantages of the newer technologies, some farmers do not adopt these technologies. This is true even when the output (e.g. yield) tends to be better compared with the output achieved by traditional technologies. Why do some farmers not adopt new technology?

Previous studies have attempted to explain this phenomenon by credit constraints (Croppenstedt et al., 2003; Karlan et al., 2012), learning effects (Besely and Case, 1993; Conley and Udry, 2010; Foster and Rosenzweig, 1995; Munshi, 2004), accessibility of weather forecasting (Rosenzweig and Udry, 2013), lack of insurance markets and capital markets (Karlan et al., 2012) and heterogeneity in the cost and benefit of technologies (Suri, 2011). More recent studies have attempted to answer the question through the position of behavioral economics. Duflo et al. (2011) revealed that naïve farmers are unlikely to adopt fertilizers in Kenya because they cannot solve the problem of self-commitment. Since external factors (e.g. weather, pest damage) influence the output of agricultural production, agricultural production entails production risk. Farmers' risk attitude is an important determinant in the decision-making of technology adoption in the theoretical model (Feder, sdeterminant of technological adoption (Koundouri et al., 2006; Liu, 2013; Liu and Huang, 2013). However, the literature on how the risk attitude of farmers affects technological adoption is insufficient.

We aimed to fill the gap in the empirical evidence in the literature by analyzing the effect of farmers' risk attitude on decision-making regarding the adoption of different technologies. We focused on two types of technologies. The first is a new technology entailing high risk and uncertainty in its function at the initial stage of introduction (Technology A in Fig. [1]). For example, a new seed variety is categorized in Technology A. While external factors (e.g. weather, soil conditions) determine its yield, farmers do not know the exact distribution of outcome in their own farming land at the time of its introduction due to a lack of experience of agricultural production using the new seed variety. Owing to the process of learning from their own experience and that of other farmers, the risk and uncertainty decreases over time (Technology A' in Fig. [1]). The second is a new technology involving low risk and uncertainty in its function at the time of introduction (Technology B in Fig. [1]) since external factors do not affect its function. Because of limited data, we analyzed the effect of farmers' risk attitude on the adoption of Technology A' and Technology B. Thus, we refer to the result of Liu (2013), which reveals how risk attitude affects the timing of adoption of a technology such as Technology A in Fig. [1], using data on cotton farmers in China.

Why do we need to analyze the effect of farmers' risk attitude on the decision to adopt different technologies? There are two answers. One is that several technologies entail different types of uncertainty and risk. Thus, the effect of farmers' risk attitude might vary across technologies and the timing of their introduction. For example, in the case of a new rice variety, both exogenous factors such as the weather and the characteristics of the farming land (e.g. irrigation system and soil quality) determine its yield. In addition, owing to lack of experience of agricultural production using the new rice variety, farmers cannot accurately predict the yield (how the new rice variety seeds grow on their own farming land) at the time of its introduction. In other words, farmers face exogenous risk and uncertainty such as the weather as well as risk and uncertainty in the variety's yield. Farmers learn to predict the yield from their own experience as well as that of other farmers. Risk and uncertainty in the function of a new technology decrease over time. In contrast with such a new variety seed, measuring machines (e.g. thermometer, moisture meter) are technologies whose function is not affected by external factors and circumstances. Farmers know the exact function of the technology before they decide whether to adopt it. Since types of risk and uncertainty faced by farmers at the time of decision-making on technological adoption vary across different technologies and the timing of their introduction, the effect of farmers' risk attitude may also vary across different technologies and their timing of introduction.

Second, farmers' risk attitude correlates with other farmers' characteristics. For example, Tanaka et al. (2010) showed that risk attitude correlated with educational level and age in a rural area in Vietnam. The evidence indicates that we cannot separately identify the effects of other variables from the effect of preferences without controlling these preferences in estimated equations.

Our study is based on a survey of rice farmers conducted in Cambodia. The International Rice Research Institution (IRRI) has implemented this survey aimed at improving living standards in rural areas in Cambodia since 2005. We conducted a survey of the rice farmers in 20 villages in four provinces (Battambang, Prey Veng, Pursat, and Takeo) from December 2012 to January 2013 as a part of an assessment of the post-harvest technologies interventions of IRRI. Thus, we collected information of usage conditions of technologies that IRRI provided lately as well as that on rice farming activities during the past one year.

In this study, we considered two types of technologies: moisture meter and a modern variety of rice seed. A moisture meter is a post-harvest technology recently introduced by IRRI and corresponds to Technology B in Fig. [1]. The moisture meter allows farmers to know the moisture content of rice accurately. External factors (e.g. weather, humidity) do not affect its function. The moisture content of seeds affects their germination rate (IRRI, 2008). Before its introduction, farmers measured the moisture content by themselves. They checked the moisture content by biting the seeds or feeling by hand. However, with these manual methods, risk and uncertainty exist because the farmers might measure the moisture content inaccurately. The moisture meter resolves the risk and uncertainty regarding the moisture contents of seeds. Modern varieties of rice seeds (compared to traditional varieties) were introduced in Cambodia in the 1990s. The modern variety of rice seed has a higher tolerance compared to the traditional variety of seed. Farmers can sow the modern variety of seed in all three agricultural seasons (dry, early wet and wet seasons). Since agricultural production is affected by external factors (e.g. weather, soil quality) and farmers cannot predict its yield at the time of its introduction, the modern variety of seed entails risk and uncertainty for farmers at the time of its introduction. Owing to the process of learning from their own experience and that of other farmers, risk and uncertainty regarding its yield are reduced over time. Thus, the modern variety of rice seed corresponds to Technology A' in Fig. [1].

We incorporated prospect theory (PT) into the utility function of farmers. In the utility function, risk aversion (concavity of agents' value function), loss aversion (degree of agents' sensitivity to loss compared to gain) and nonlinear probability weighting (how an agent overestimates a small (large) probability and underestimates a large (small) probability) determine the shape of the utility function (Kahneman and Tversky, 1979). The utility function, thus, is distinct from the expected utility (EU), which parameterizes the risk aversion of the utility function as risk attitude. Why do we need to incorporate PT into the utility function of farmers? One possible answer is that the degree of risk aversion alone is not sufficient to express the effect of risk attitude on technological adoption since agricultural activities entail several types of risk and uncertainty. In addition, farmers implicitly set a target income[1] for earning subsistence income under the risk and uncertainty. In fact, Liu (2013) showed that loss aversion, nonlinear probability weighing and risk aversion affected the timing of adoption of a new cotton variety seed (*Bacillus thuringiensis* cotton: BT cotton, which has the same quality as the traditional cotton variety and controls pest damage without the use of pesticides).

Following the method of Tanaka et al. (2010), we asked virtual questions regarding the preference of lotteries to elicit the farmers' risk preferences in the interviews. Applying this method, we estimated three components of utility function: risk aversion, loss aversion and nonlinear probability weighting. Since Liu (2013) also applied this method, we could compare the effect of farmers' risk preferences across technologies.

As expected, the effects of risk preferences on technological adoption varied across these technologies. Risk averse farmers and farmers who overestimate a small probability used the moisture meter for measuring the moisture contents of seeds. However, with respect to the modern variety, there was no effect of farmers' risk preferences. Rather, the choice of variety was largely determined by other household characteristics and type of irrigation. Our results imply the types of risk and uncertainty faced by farmers at the time of decision-making on technological adoption partly influence the outcomes of risk preferences.

The rest of the paper is organized as follows. Section 2 reviews in detail the agricultural technologies on which we focused. Section 3 explains the survey design and the experiment in the study. Section 4 presents econometric analysis using household level data. Section 5 discusses our results and compares them with the results of previous studies. The last section provides conclusions.

2. Background

2.1 Moisture Meter

IRRI has provided post-harvest technologies[2] for improving farmer's living standards in rural areas in Cambodia. In Battambang and Prey Veng, the first (or old) moisture meters were provided in February 2008. These moisture meters were made by IRRI (low cost, unreliable and did not last long). New moisture meters were introduced to these two villages in January 2012 and the same type of moisture meter was simultaneously introduced to two other provinces: Pursat and Takeo. This newer moisture meter is digital and is made in Japan or South Korea (accurate but relatively expensive). Therefore, the timing of introduction of the technology varied across provinces. One set of moisture meters was distributed to two representatives of farmers in each treatment village and one of the representative farmers kept the moisture meter in each village. They were required to set up an inception meeting to teach farmers how to use the post-harvest technologies, and to lend each item to farmers if required.

Fig. [2] shows a photo of the moisture meter provided by IRRI in January 2012. Farmers can measure the accurate moisture content of rice easily by using the moisture meter. Owing to the simplicity of its function and the explanation given at the inception meeting, farmers could learn how to use it easily. Moisture is one of the most important indicators for checking whether the seeds are being appropriately managed; the germination rate of seeds greatly depends on the moisture content (IRRI, 2008). In fact, 42.7% of farmers used a moisture meter to measure the moisture content of seeds in our sample (Table [1]). Since farmers measured the moisture content by biting or by hand before its introduction, risk and uncertainty existed in measuring the moisture content. The moisture meter contributed to reducing the risk and uncertainty.

2.2 Modern Variety of Rice

Broadly speaking, there are two varieties of rice seed: the traditional variety of seed (hereafter TV) and the modern variety of seed (hereafter MV). TV is an indigenous variety of seed that farmers have used for a long time. MV is a hybrid variety of seed introduced in the 1990s (FAO, 2002). The function of MV differs from that of TV. In particular, owing to the difference of tolerance between MV and TV, farmers can plant MV in a rainless season with appropriate water management. In Cambodia, there are three farming seasons: dry season, early wet season and wet season. While farmers can grow MV in all seasons, farmers can grow TV in only the wet season each year. According to our data collected in four provinces in Cambodia, few farmers planted TV in the dry and early wet season (Table [2]).

In the wet season in 2012, approximately 90% of plots in our sample were planted with TV[3]. The selling price of TV is higher than that of MV. For this reason, many farmers might plant TV. Also, the planting period of MV is shorter than TV and MV is more tolerant to adverse weather conditions than TV.

Since external factors (e.g. weather, soil quality) affect the yield of rice production and farmers do not understand its function at the time of its introduction, risk and uncertainty in its function are expected at the time of its introduction. However, over the long term (about 20 years), the risk and uncertainty have reduced owing to the process of learning from their own experience and that of other farmers.

3. Data

3.1 IRRI Survey

We carried out a farmers' survey in 20 villages in four provinces (Battambang, Prey Veng, Pursat, and Takeo) to assess the post-harvest technologies interventions IRRI implemented for improving living standards in rural areas in Cambodia. The survey was conducted from December 2012 to January 2013. This period corresponded to the period after the wet season when almost all farmers in Cambodia are engaged in rice farming. We collected a variety of information: usage conditions of post-harvest technologies, agricultural activities during the past year, social and demographic characteristics, respondent preferences, and non-agricultural income sources.

In the survey, we invited farmers selected randomly in each village to a public place of the village and allocated an enumerator to each farmer. In the interview, each enumerator started the interview at a distance from other enumerators to avoid the influence of another farmer's answer. Since we focused on the risk preferences of individuals who were involved in decision-making on agricultural adoption, we requested that the selected farmers should be the household head or the head's wife. The enumerators basically asked the respondents each question orally to avoid misunderstanding. The respondents received a gift at the end of the interview.

We did not collect information on rice production from the representatives of each village. Instead, we interviewed the representatives and obtained information about the village in detail (e.g. experience of natural disasters).

There were two types of villages: treatment villages and control villages. While the former villages received the post-harvest technological equipment from IRRI, the latter villages did not. We collected the same information on input and output for rice-farming activities in both the treatment village and the control village. On the other hand, information on the usage of the post-harvest technology was collected at the treatment villages only. Thus, while we could use data of both groups in the analysis of rice variety choice, we restricted the data to that collected in the treatment villages in the analysis of adoption of a moisture meter[4].

While not all farmers were engaged in rice farming during the dry season and the early wet season, almost all of the farmers planted rice in the wet season. Farmers can choose whether to plant TV or MV in the wet season. Thus, we focused on rice farming in the wet season.

Although we surveyed 349 households, 19 households could not be used because the respondents were not a head of household or the head's wife. In addition, because of missing data and outliers, only 238 samples were used. Table [3] shows descriptive statistics of the sample. The first three preference parameters are explained later in the subsection on how to measure risk preferences. The average age of the head was 48.5 years old. A household head had finished approximately 5 years of education on average. 78.2% of the household heads were male. The average maximum years of schooling was 9.2 years, which is approximately two times the average years of schooling of the household head. This seems to reflect the recent growth in the number of years of schooling of young people owing to the introduction of free education after the collapse of the *Pol Pot* regime. Approximately 16% of heads gained their income from non-agricultural work and the average total non-agricultural income in households in the past year was 4.4 million *riel*[5]. The average total earnings from rice farming in the dry and early wet season was 0.9 million *riel*. The average total amount of rice in storage for selling in the dry and the early wet seasons and the average total amount for self-consumption in the dry and the early wet seasons were 114.3 *kg* and 347.3 *kg*, respectively. Farmers who were engaged in rice farming in the dry or the early wet season kept a larger amount of rice for self-consumption than for selling. With respect to the usage of a moisture meter, 42.7% of farmers adopted it to measure the moisture content of seeds in the wet season. On average, the usage rate of the moisture meter by the other farmers in the same village in the wet season in 2012 was around 37.8%[6].

Since the characteristics of the plot might affect farmers' crop choice, we used a sample plot for analysis of crop choice to control for plot characteristics. The survey collected detailed information on the plots such as area, type of soil, source of irrigation and elevation. Table [4] displays descriptive statistics of the plots. The average area of a plot was 0.8 hectare. Regarding the type of soil, 77.8% of plots were loam, 21.5% of plots were clay, 2.5% of plots were sandy, and 2.5% of plots were other. 82.8% of plots were located at a middle elevation, 6.6% of plots were located at a high elevation and 10.6% of plots were located at a low elevation. No irrigation system was installed on 70.7% of plots. Few plots had irrigation systems (deep wall pumps/shallow tube wells/pumped from rivers, canals, dams).

3.2 How to Measure Risk Preferences

To elicit farmers' risk preferences, we asked hypothetical questions regarding preferences at the beginning of each interview. Following the experiment of Tanaka et al. (2010), we examined the attitude of respondents by using a pair-wise lottery of both risky and safer alternatives as shown in Table [5]. For example, a farmer faces the following choice at row 1 in series 1: in Lottery A which is a safer choice than B, the respondent can receive 40,000 riel with a probability of 70% and the respondent can receive 10,000 riel with a probability of 30%: in Lottery B, which is a riskier choice than A, the respondent can receive 68,000 riel with a probability of 10% and the respondent can receive 5,000 riel with a probability of 90%. Although both the probability of winning and the amount of winning in Lottery A do not change, only the amount of winning in Lottery B increases with the number of rows. However, in series 3, both the probability and the amount of winning change in Lottery A and Lottery B.

We requested the enumerators to ask each respondent to choose either Lottery A or Lottery B for each row until the respondent switched from Lottery A to Lottery B in each series. For example, if the respondent shifted from Lottery A to Lottery B at row 6 in series 1, the enumerator started to ask series 2.

In this study, we assumed farmers have the following utility function. This utility function was proposed by Tanaka et al. (2010).

$$U(x,p;y,q) = \begin{pmatrix} v(y) + \pi(p)\big(v(x) - v(y)\big) & for\ xy > 0\ and\ |x| > |y| \\ v(y) + \pi(p)v(x) + \pi(q)v(y) & otherwise \end{pmatrix} \quad (1)$$

where p and q are the probability of outcomes x and y, respectively; the value function is defined as $v(z) = z^{\sigma}$ for $z > 0$, $v(z) = \lambda z^{\sigma}$ for z<0, where $z = x, y$; the probability weighting function is given by $\pi(p) = 1/\exp\ [\ln\ (1/p)]^{\alpha}$. Parameters σ and λ are the measure of risk-aversion and the measure of loss aversion. A lower σ means a more risk-averse individual. If $\lambda > 1$, the individual feels more sensitive to a loss. If $\alpha < 1$, the weighting function is inverse S-shaped, which means that the individual esteems a small probability and devalues a high probability. If $\alpha > 1$, the weighing function is S-shaped, which means that the individual devalues a small probability and esteems a high probability. In the case of $\lambda = 1$ and $\alpha = 1$, the utility function equals the standard expected utility function. We computed three parameters λ, σ and α using the switching points of respondents in the three series in Table [5]. Following the previous studies, we did not use the sample of respondents who did not switch from Lottery A to Lottery B. Descriptive statistics of these parameters are listed in Table [3]. We tested the null hypothesis that $\lambda = 1$ and $\alpha = 1$ using the computed parameters of each of the farmers, and rejected the hypothesis at the 1% significance level.

4. Econometric frameworks and regression results

4.1 Use of the Moisture Meter for Seeds

First, we considered the decision-making on adoption of a moisture meter to measure the moisture content of seeds. Since almost all the farmers were engaged in rice farming in the wet season, we focused on the adoption of a moisture meter in the wet season. As explained in Section 2.1, the use of a moisture meter reduces the risk and uncertainty in measuring the moisture contents of seeds. When farmers borrow a moisture meter from the representative in each village, the farmers must bear any cost of borrowing (e.g. contact, transplantation). How farmers evaluate the occasion of measuring the moisture contents inaccurately will determine the effects of farmers' risk preference on its adoption. Our hypothesis is that farmers who fear the occasion, farmers who overestimate the occasion and farmers who care about the loss of mismeasuring the moisture contents (e.g. low germinant rate) tend to adopt the moisture meter.

To test the hypothesis, we first estimated the following model by applying a linear probability model,

$$\text{Moisture}^*_{\text{iv}} = \delta_0 + \delta_1\sigma_{\text{iv}} + \delta_2\lambda_{\text{iv}} + \delta_3\alpha_{iv} + \mu_p + \varepsilon_{iv} \qquad (2)$$

where i denotes farmer, and v denotes village; $Moisture^*_{iv}$ takes 1 if farmer i in village v uses the moisture meter in the wet season and takes 0 if farmer i in village v does not use the moisture meter. σ_{iv} is the degree of risk aversion of farmer i in village v and λ_{iv} is the degree of loss aversion of farmer i in village v. α_{iv} is the degree of probability weighting of farmer i in village v and μ_p is a province fixed effect. ε_{iv} is the unobservable error term. If our hypothesis is correct, the signs of δ_1 and δ_2 will be negative and the sign of δ_3 will be positive.

We did not control for the village fixed effects in Eq.(2) since unobservable characteristics (e.g. weather, quality of soil) are unlikely to affect whether farmers used the moisture meter for seeds. However, as mentioned above, the timing of introduction of post-harvest technologies differed across provinces. To control for the effect, we added province fixed effects in the equation.

The results of the estimation using Eq.(2) are presented in Column(1) in Table [6]. The coefficients of province fixed effect are not shown in the table due to space limitations. As expected, a farmer who esteems a small probability and who is more risk averse is more likely to use the moisture meter for seeds, and these are statistically significant at the 5 percent level. However, the parameter of loss aversion does not affect the adoption significantly. The results imply that risk averse farmers who fear measuring the moisture content accurately and farmers who overweight the probability of measuring the moisture contents inaccurately adopted the moisture meter. Thus, how farmers worry about measuring the moisture content of seed inappropriately is closely related to the adoption of the moisture meter for seeds.

However, other factors might affect not only the use of the moisture meter, but also farmers' risk preferences. In that case, we cannot distinguish the effect of risk preferences from the effect of other factors. Tanaka et al. (2010) showed that the degree of risk aversion was negatively correlated with educational level in a rural area in Vietnam. Then, if educational level were correlated with the adoption of the moisture meter, parameters of risk preferences would be biased. In addition, other farmers' decisions regarding the adoption of the moisture meter would affect the decision-making. To control for these effects, we considered the following linear probability model.

$$Moisture_{iv}^{*} = \delta_0 + \delta_1\sigma_{iv} + \delta_2\lambda_{iv} + \delta_3\alpha_{iv} + \xi X_{iv} + \mu_p + u_{iv} \qquad (3)$$

where X_{iv} is a vector of the characteristics of farmer *i* in village *v*; such as the characteristics of the head (age, education, sex), maximum education in household, earning from non-agricultural work, and moisture meter usage rate of other farmers in village v; u_{iv} is the unobservable error term.

The moisture meter usage rate of other farmers allows us to control for not only the effect of accessibility to a moisture meter in each village but also the effect of the externality from other farmers. As explained by Besely and Case (1993), we cannot identify the effect of the externality from other farmers accurately by using cross sectional data since its estimator is influenced by the effects of both accessibility and externality at the same time.

Column (2) shows the results of estimation by Eq.(3). The effect of risk preferences is consistent with the results of estimation by Eq.(2). Educated heads are more likely to use the moisture meter to measure the moisture content of seeds, and the coefficient of this variable is statistically significant at the 1 percent level. Farmers who earn more non-agricultural income are less likely to use the moisture meter for seeds and that is statistically significant at the 10 percent level. We found that the amount of rice saved for seed does not affect the decision of whether to use the moisture meter. This implies that the amount of seed is not an important factor in determining the use of the moisture meter. The coefficient of the moisture meter usage rate of other farmers is positive, implying the presence of externality or learning from others, but it is not statistically significant.

4.2 Variety Choice

Secondly, we focused on the decision concerning the choice of rice variety. Since almost all of the farmers are engaged in rice farming in the wet season, we also focused on the decision regarding the choice of rice variety in the wet season. The risk and uncertainty in the function of MV is expected to be low. We assumed that farmers know the function and profitability of each variety in their plots. However, farmers might face exogenous risk (e.g. drought) and uncertainty in rice production. Thus, how farmers evaluate the occasion of exogenous risk (e.g. drought) will determine the effects of farmers' risk preference in deciding which variety of rice to choose. Our hypothesis is that farmers who fear drought, and who overestimate the possibility of drought, and who care about the loss caused by drought would tend to adopt MV, which has higher tolerance compared to TV.

To test this hypothesis, we estimated the following model by applying the linear probability model,

$$Modern\ Variety^{*}_{ijv} = \beta_0 + \beta_1\sigma_{iv} + \beta_2\lambda_{iv} + \beta_3\alpha_{iv} + \gamma X_{iv} + \mu_v + \varepsilon_{ijv} \qquad (4)$$

where *i* denotes farmer, *j* denotes plot, and *v* denotes village; $Modern\ Variety^{*}_{ijv}$ takes 1 if farmer *i* in village *v* adopts MV in plot *j* in the wet season, and takes 0 if farmer *i* in village *v* adopts TV in plot j in the wet season otherwise. σ_{iv} is the degree of risk aversion of farmer i in village v and λ_{iv} is the degree of loss aversion of farmer i in village v. α_{iv} is the degree of probability weighting of farmer i in village v and X_{iv} is a vector of the characteristics of farmer i in village v, such as the characteristics of the head (e.g. age, education, sex), maximum education in household member of household i, whether the head earns from non-agricultural income, total earning from non-agricultural work, whether farmer i borrowed money for rice farming during the past year and earning/harvesting from rice farming in dry/early wet season. μ_v captures the village fixed effects and ε_{ijv} is the unobservable error term. If our hypothesis is correct, the signs of β_1 and β_2 should be negative and the sign of β_3 should be positive.

Previous studies have shown a significant effect of the externality from other farmers on the adoption of a new technology (Conley and Udry, 2010; Foster and Rosenzweig, 1995; Munshi, 2004). However, this is not necessarily the case for the choice of rice crop in Cambodia. Cambodian farmers may have sufficient knowledge about the crop varieties because they have been growing them for a long time in Cambodia.

Another possible channel would be that farmers are likely to choose the same crop variety as other farmers. For example, the agricultural union in each village encourages farmers to use MV. According to our interviews of village leaders in selected villages, however, the agricultural unions may not be functioning effectively in Cambodia for historical reasons[7]. Thus, the influence of unions may be limited.

The weather is thought to influence the choices. According to our interview with the village leaders in the selected villages, several farmers switched from TV to MV after an incidence of drought. In our estimation, we tried to control the effects of natural disaster by adding village fixed effects.

As mentioned in Section 2.2, the selling price of TV is higher than that of MV. Thus, farmers planning to sell their harvest may prefer to plant TV. While we cannot test the effect of the selling price on the rice variety choice in our analysis, the village fixed effects allow us to control the effect of the selling price[8].

Column (1) in Table [7] shows the results of estimation by Eq.(3). Due to space limitations, we omitted the coefficients of the village fixed effect from the table. Except for the estimator of loss aversion, the signs of risk preferences are consistent with our hypothesis. The signs of the estimated parameter imply that farmers who worry about drought, farmers who overweight the incidence of drought tend to use MV and loss averse farmers tend to adopt TV. However, our hypothesis is not supported statistically. In other words, the decision-making on crop choice is not determined by farmers' risk preferences. Male heads are more likely to adopt MV than female heads. While total earnings from rice farming in the dry season and the early wet season are significantly negatively correlated with the probability of adoption of MV, the total amount of rice stored for self consumption in the dry and the early wet seasons significantly increases the probability. It implies that farmers change their choice of variety based on the harvest in the previous seasons.

In our sample, some farmers plant different varieties in different plots. This implies that farmers flexibly adjust to the characteristics of their plot (e.g. quality of soil, the irrigation system and elevation). To control these possibilities, we modified Eq.(4) as follows:

$$Modern\ Variety^{*}_{ijv} = \beta_0 + \beta_1\sigma_{iv} + \beta_2\lambda_{iv} + \beta_3\alpha_{iv} + \gamma X_{iv} + \delta Z_{ijv} + \mu_v + u_{ijv} \quad (5)$$

where Z_{ijv} is a vector of characteristics of a plot. u_{ijv} is the unobservable error term. The results of estimation by Eq.(5) are shown in column (2) in Table [7]. We omit the coefficients of the village fixed effects from the table due to space limitations.

The sign of estimator of loss aversion switches from negative to positive in Eq.(5). This is consistent with our hypothesis. The sign implies that loss averse farmers tend to use MV. However, no estimated parameters of risk preferences significantly affect the probability in Eq.(5) along with the result of the estimation of Eq.(4). Thus, our hypothesis is also rejected. By considering the plot characteristics in the analysis, the effects of some variables became significant. Farmers who earn more income from non-agricultural work are more likely to adopt TV, and the coefficient of this variable is statistically significant at the 10 percent level. Among the characteristics of plot, the crop choice decision is not affected by soil quality and elevation. In contrast, farmers choose MV significantly in the plots that have access to water for agriculture pumped from rivers/canals/dams.

Robustness check

As mentioned above, some farmers adopted both MV and TV in their plots. In those who adopted both MV and TV, some farmers dispersed the yield risk (e.g. drought) by adopting multiple varieties. However, this means we cannot identify the effect of farmers' risk preference on the adoption of MV from the effect of farmers' risk preference on risk diversification through crop diversification. To remove the latter effect, we ignored samples of farmers who adopted both MV and TV in their plot, and used Eq.(5) to re-estimate. We show the results of estimation in column (3) in Table [7]. The results have not changed dramatically although some control variables such as the characteristics of farmers became insignificant. This confirms that our main arguments still hold.

5. Discussion

Our results contrast with those of Liu (2013). Liu (2013) focused on the relationship between the farmers' risk preferences and the timing of adoption of *Bacillus thuringiensis* (BT) cotton in a rural area in China. BT cotton, which is a new cotton variety with the same quality as the traditional cotton variety, allows farmers to control pest damage without pesticides. However, risk averse farmers who used BT cotton continued to use pesticides (Liu and Huang, 2013). This is because the farmers did not fully understand the function of the new technology. Furthermore, risk averse farmers were concerned about the possibility of pest damage. Following Tanaka et al. (2010), she also conducted an experiment to elicit the farmers' risk preferences and revealed that farmers who feared yield loss or yield risk adopted BT cotton later since the farmers did not have sufficient knowledge of BT cotton while farmers who overweight the probability of pest damage adopted BT cotton earlier. Although agricultural production is affected by external factors (e.g. weather, pests) as well as the characteristics of the plot (e.g. soil quality, irrigation system), farmers cannot access exact information on how a new variety seed such as BT cotton will grow in their plot at the initial stage of introduction. The production of new variety seed entails not only exogenous risk and uncertainty but also risk and uncertainty in its function at the stage of introduction. Thus, BT cotton corresponds to Technology A in Fig. [1]. Liu's (2013) results are concerned with the implications of risk preference on new technology when mixing two types of risk and uncertainty at the time of decision-making.

Why do farmers' risk preferences affect agricultural choices differently? One possible answer is the different type of risk and uncertainty that farmers face at the time of decision-making on technological adoption. A moisture meter does not entail risk and uncertainty in its function since the moisture meter allows farmers to measure the moisture content of seeds accurately at any time. In fact, the surveyed farmers learned its function from the representative in each village at the inception meeting. A moisture meter is equivalent to Technology B in Fig. [1]. However, farmers still face risk and uncertainty in the accuracy of measuring the moisture content when they measure the moisture content of seeds by themselves. We found that risk averse farmers and farmers who overestimate a small probability tended to adopt the moisture meter since they were afraid of mismeasuring the moisture content of seeds. The different effect of risk preference on the agricultural technological adoption might be caused by the type of risk and uncertainty that farmers face when they make a decision on technological adoption.

This interpretation is supported by our analysis of choice of rice variety. Risk and uncertainty in the function of MV are high at the time of introduction like BT cotton in China because external factors affect its function and farmers cannot access information on the function of MV in their plot. One of the differences between MV and BT cottons is its timing of introduction. Since farmers can learn about new technology from their own experience as well as that of other farmers, the degree of risk and uncertainty of MV became lower over time. In addition, since we focused on the wet season, natural disasters such as drought are unlikely to occur. Exogenous risk and uncertainty is expected to be low. In contrast to Liu (2013), we found that risk preferences did not determine the adoption of MV statistically. Since farmers know the function of MV and there are no exogenous risk and uncertainty, they make the optimal choice on variety based on other factors (e.g. characteristics of plot, function of technology).

6. Conclusion and Policy Implications

In this paper, we investigated the effect of farmers' risk preferences on the adoption decision across various types of technology. We conducted virtual questions following Tanaka et al. (2010) in order to elicit the farmers' risk preferences, which cannot be observed directly. We considered the adoption of two types of agricultural technology: the use of a moisture meter and a modern rice variety (compared to the traditional variety). The moisture meter is a new technology introduced lately by IRRI and allows farmers to know the exact moisture content of rice at any time. The modern rice variety is a technology that has been prevailing widely for a long time. Risk and uncertainty in the function of MV existed at the time of its introduction and decreased over time. We found that risk averse farmers and farmers who overestimate small probabilities tended to use the moisture meter to measure the moisture contents of seeds. In contrast, we found that farmers' risk preferences were not important factors in the choice of rice variety. The effects of farmers' risk attitude on technological adoption varied across different technologies and the timing of their introduction because types of risk and uncertainty differ at the time of decision-making on technological adoption.

There are two policy implications. First, if the timing of technology adoption differs among people depending on their preferences, a quick assessment of a project using standard empirical program evaluation methodologies might miss the full impact of the project. For instance in our context, risk averse farmers initially start using a moisture meter and the appropriate moisture content of seeds improves the germination rate. However, over time, less risk averse people would start using a moisture meter. Thus, the timing of assessment of such a project apparently affects the estimated outcome, hence the evaluation of the project. Many studies that evaluate programs measure the relatively short-run effects of a project. But, our results suggest that people really need to know the relatively long-run effects of a project. Second, if policymakers plan to diffuse a technology that does not entail risk and uncertainty in its function (MV corresponds to this case in our context), it would be more productive to remove obstacles and bottlenecks that farmers routinely face such as improvement of the irrigation system.

Footnotes

1. The existence of a target income in the agricultural context has not been tested formally. However, many studies have shown evidence of a target income in various scenarios (Cameror et al., 1997; Farber, 2008; Fehr and Goette, 2007).

2. The post-harvest technologies provided in the project included: Combine harvesting services, mechanical dryers, hermetic storage systems (especially, 50 kg Super bags (SB)), granary improvements, rice milling improvements, moisture meter, weighing scales, cleaner and thermometer.

3. According to our interview with agricultural experts during our inception trip to the study area, Cambodians prefer to eat TV rice rather than MV rice because TV rice is tastier than MV rice.

4. The averages of some variables differ significantly between treatment villages and control villages. However, this does not affect our analysis because we do not compare the treatment villages with the control villages in our analysis.

5. As of 31 December 2012, US$1 was equivalent to 3,909.4 Cambodian Riel.

[6] $the\ other\ farmers'\ usage\ rate\ of\ moisture\ meter_{iv} = \sum_{i \neq j}^{N_v} usage\ of\ moisture\ meter_j\ /\ N_v$,

where i is farmer i; v is village v; $usage\ of\ moisture\ meter_j$ is a variable, which indicates whether farmer j adopted the moisture meter to measure the moisture content of seeds; N_v is the number of samples in a village.

[7] Anecdotally, some agricultural unions are said to have contributed to the mass killings during the *Pol Pot* administration.

[8] Farmers usually sell their surplus of harvested rice to grain traders at their village. The entry of grain traders is limited in the local market since the entry cost of buyers is high (e.g. They must bear fixed costs such as those for storage facilities, vehicles for transportation as well as running transportation costs such as gas or access to credit to purchase agricultural goods.). Monopsony by grain traders occurs in the local market. Since the selling price is partly determined by the degree of the monopsony power of grain traders in their villages, village fixed effects partly allow us to control the monopsony power of buyers in the villages.

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Table 1. Usage of moisture meter in wet season in 2012

	Sample	usage rate
Whether farmers use moisture meter in wet season in 2012	150	43.3%
Purpose: to measure moisture content of		
seeds	150	42.7%
rice for sale	150	11.3%
rice for own consumption	150	15.3%
rice for storage	150	8.7%

Table 2. Number of usage of MV and TV in each season

	Dry Season	Early Wet season	Wet season
Modern Variety	100	73	43
Traditional Variety	3	6	353

Note: unit is plot.

Table 3. Descriptive statistics of household

Variable	Sample	Mean	Std.Dev
preference parameters of respondent			
σ (Value function curvature)	238	0.994	0.428
λ (Loss aversion)	238	1.715	1.600
α (Probability weighting)	238	0.652	0.214
characteristics of household			
age of head	238	48.534	12.303
education of head (years)	238	5.025	3.121
maximum education in household (years)	238	9.155	3.478
sex of head (1=male, 0=female)	238	0.782	0.414
number of family members	238	5.395	2.024
whether head earns from non-agricultural work	238	0.160	0.367
years of farming	238	27.651	12.819
total non-agricultural income (riel)	238	4389215	5442374
agricutural activity			
whether farmer borrows money for rice farming in the past year	238	0.282	0.451
total earning from rice farming in dry and early wet season (riel)	238	914628	2131897
total amount of rice kept for selling in dry and early wet season (kg)	238	114.286	691.031
total amount of rice kept for self consumption in dry and early wet season (kg)	238	347.252	690.577
usage of moisture meter			
whether farmer uses moisture meter for seed in wet season in 2012 (Yes=1,No=0)	150	0.427	0.496
other farmers' usage rate of moisture meter for seed in village in wet season in 2012	150	0.378	0.125

Table 4. Descriptive statistics of plot

Variable	Sample	Mean	Std.Dev
area (ha)	396	0.796	0.899
type of soil			
clay	396	0.215	0.411
sandy	396	0.025	0.157
other	396	0.025	0.157
loam	396	0.778	0.416
elevation			
high	396	0.066	0.248
middle	396	0.828	0.378
low	396	0.106	0.308
type of irrigation system			
deep wall pump	396	0.028	0.165
shallow tube well	396	0.020	0.141
pumped from river/canal/dam	396	0.273	0.446
none/rainfall	396	0.707	0.456

Table 5. Payoff of lottery

Lottery A	Lottery B
Series 1	
1 70% winning 40,000 riel and 30% winning 10,000 riel	1 10% winning 68,000 riel and 90% winning 5,000 riel
2 70% winning 40,000 riel and 30% winning 10,000 riel	2 10% winning 75,000 riel and 90% winning 5,000 riel
3 70% winning 40,000 riel and 30% winning 10,000 riel	3 10% winning 83,000 riel and 90% winning 5,000 riel
4 70% winning 40,000 riel and 30% winning 10,000 riel	4 10% winning 93,000 riel and 90% winning 5,000 riel
5 70% winning 40,000 riel and 30% winning 10,000 riel	5 10% winning 106,000 riel and 90% winning 5,000 riel
6 70% winning 40,000 riel and 30% winning 10,000 riel	6 10% winning 125,000 riel and 90% winning 5,000 riel
7 70% winning 40,000 riel and 30% winning 10,000 riel	7 10% winning 150,000 riel and 90% winning 5,000 riel
8 70% winning 40,000 riel and 30% winning 10,000 riel	8 10% winning 185,000 riel and 90% winning 5,000 riel
9 70% winning 40,000 riel and 30% winning 10,000 riel	9 10% winning 220,000 riel and 90% winning 5,000 riel
10 70% winning 40,000 riel and 30% winning 10,000 riel	10 10% winning 300,000 riel and 90% winning 5,000 riel
11 70% winning 40,000 riel and 30% winning 10,000 riel	11 10% winning 400,000 riel and 90% winning 5,000 riel
12 70% winning 40,000 riel and 30% winning 10,000 riel	12 10% winning 600,000 riel and 90% winning 5,000 riel
13 70% winning 40,000 riel and 30% winning 10,000 riel	13 10% winning 1,000,000 riel and 90% winning 5,000 riel
14 70% winning 40,000 riel and 30% winning 10,000 riel	14 10% winning 1,700,000 riel and 90% winning 5,000 riel
Series 2	
1 90% winning 40,000 riel and 10% winning 30,000 riel	1 70% winning 54,000 riel and 30% winning 5,000 riel
2 90% winning 40,000 riel and 10% winning 30,000 riel	2 70% winning 56,000 riel and 30% winning 5,000 riel
3 90% winning 40,000 riel and 10% winning 30,000 riel	3 70% winning 58,000 riel and 30% winning 5,000 riel
4 90% winning 40,000 riel and 10% winning 30,000 riel	4 70% winning 60,000 riel and 30% winning 5,000 riel
5 90% winning 40,000 riel and 10% winning 30,000 riel	5 10% winning 62,000 riel and 90% winning 5,000 riel
6 90% winning 40,000 riel and 10% winning 30,000 riel	6 10% winning 65,000 riel and 90% winning 5,000 riel
7 90% winning 40,000 riel and 10% winning 30,000 riel	7 10% winning 68,000 riel and 90% winning 5,000 riel
8 90% winning 40,000 riel and 10% winning 30,000 riel	8 10% winning 72,000 riel and 90% winning 5,000 riel
9 90% winning 40,000 riel and 10% winning 30,000 riel	9 10% winning 77,000 riel and 90% winning 5,000 riel
10 90% winning 40,000 riel and 10% winning 30,000 riel	10 10% winning 83,000 riel and 90% winning 5,000 riel
11 90% winning 40,000 riel and 10% winning 30,000 riel	11 10% winning 90,000 riel and 90% winning 5,000 riel
12 90% winning 40,000 riel and 10% winning 30,000 riel	12 10% winning 100,000 riel and 90% winning 5,000 riel
13 90% winning 40,000 riel and 10% winning 30,000 riel	13 10% winning 110,000 riel and 90% winning 5,000 riel
14 90% winning 40,000 riel and 10% winning 30,000 riel	14 10% winning 130,000 riel and 90% winning 5,000 riel
Series 3	
1 50% winning 25,000 riel and 50% losing 4,000 riel	1 50% winning 30,000 riel and 50% losing 20,000 riel
2 50% winning 4,000 riel and 50% losing 4,000 riel	2 50% winning 30,000 riel and 50% losing 20,000 riel
3 50% winning 1,000 riel and 50% losing 4,000 riel	3 50% winning 30,000 riel and 50% losing 20,000 riel
4 50% winning 1,000 riel and 50% losing 4,000 riel	4 50% winning 30,000 riel and 50% losing 16,000 riel
5 50% winning 1,000 riel and 50% losing 8,000 riel	5 50% winning 30,000 riel and 50% losing 16,000 riel
6 50% winning 1,000 riel and 50% losing 8,000 riel	6 50% winning 30,000 riel and 50% losing 14,000 riel
7 50% winning 1,000 riel and 50% losing 8,000 riel	7 50% winning 30,000 riel and 50% losing 11,000 riel

Table 6. OLS regression of moisture meter use for seed

dependent variable: whether farmer uses moisture meter for measuring moisture contents of seed				
independent variables	Column (1)		Column (2)	
	Coef.	Std. Err	Coef.	Std. Err
σ (Value function curvature)	-0.240 **	0.091	-0.234 **	0.100
λ (Loss aversion)	-0.019	0.035	-0.026	0.036
α (Probability weighting)	-0.414 **	0.183	-0.373 *	0.205
age of head			-0.004	0.008
education of head (years)			0.011 ***	0.013
maximum education in household (years)			-0.022	0.022
sex of head (1=male, 0=female)			0.038	0.099
number of family members			0.012	0.022
years of farming			0.005	0.008
total non-agricultural income (log)			-0.219 *	0.115
total amount of saving for seeds (log)			-0.004	0.028
moisture meter usage rate of other farmers for seed in village			0.094	0.430
Sample size	150		146	
Adjusted R squared	0.039		0.013	

Note: 1. Standard error in parenthesis is clustered at village level. 2. All regressions include province fixed effects. 3. The unit of observations for the regression is the original farmer.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

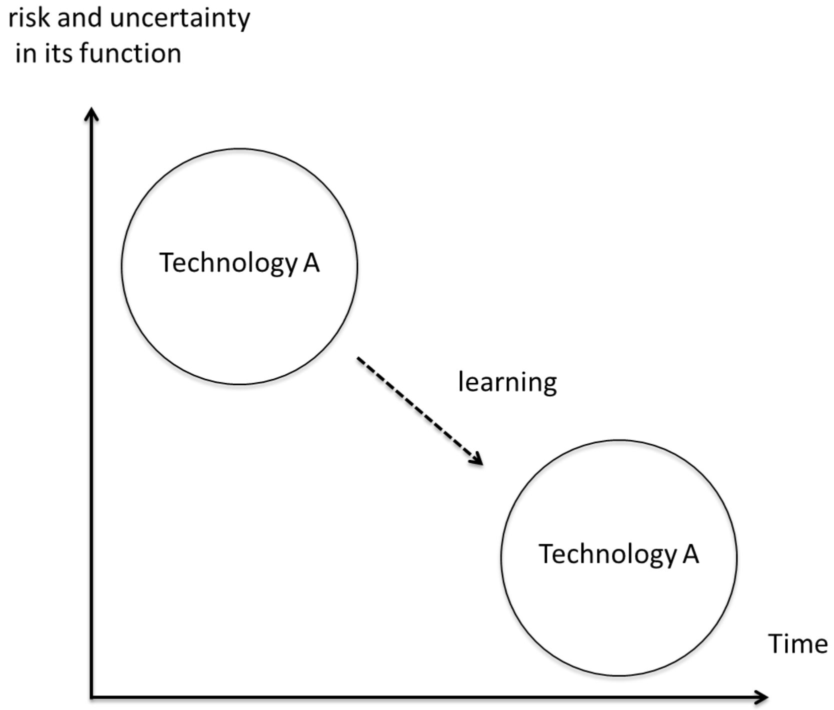
Table 7. Result for modern variety

dependent variable: whether farmer adopts a modern variety in wet season in 2012						
independent variables	Column(1)		Column(2)		Column(3)	
	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
σ (Value function curvature)	-0.015	0.030	-0.034	0.043	-0.017	0.044
λ (Loss aversion)	-0.004	0.006	0.007	0.009	0.009	0.010
α (Probability weighting)	-0.041	0.082	-0.019	0.088	-0.016	0.078
age of head	0.002	0.004	0.000	0.003	0.001	0.003
education of head (year)	0.010	0.006	0.010 *	0.006	0.008	0.005
maximum education in household (year)	-0.005	0.004	-0.011 *	0.006	-0.013 *	0.007
sex of head (1=male, 0=female)	0.070 ***	0.024	0.066 *	0.034	0.054	0.035
number of family members	0.013	0.016	0.019	0.016	0.020	0.017
whether head earns from non-agricultural work	0.044	0.048	0.046	0.053	0.025	0.062
years of farming	0.000	0.003	0.000	0.003	-0.001	0.003
total non-agricultural income (log)	-0.019	0.013	-0.020 *	0.011	-0.001	0.007
whether farmer borrows money for crop in the past year	0.063	0.052	0.053	0.050	0.050	0.056
total earning from rice farming in dry and early wet season (log)	-0.010 ***	0.003	-0.008 **	0.003	-0.007 **	0.004
total amount of rice kept for selling in dry and early wet season (log)	-0.012	0.009	-0.014	0.010	-0.006	0.010
total amount of rice kept for self consumption in dry and early wet season (log)	0.015 **	0.007	0.012 *	0.006	0.008 *	0.007
Characteristics of plot						
area (ha)			0.012	0.013	0.013	0.017
type of soil						
clay			-0.023	0.038	-0.052	0.032
sandy			0.080	0.126	0.056	0.123
other			-0.296	0.201	-0.125	0.130
elevation						
high			0.126	0.085	0.135	0.099
middle			0.027	0.028	0.026	0.033
type of irrigation system						
deep wall pump			-0.088	0.054	-0.060	0.043
shallow tube well			0.070	0.080	0.044	0.068
pumped from river/canal/dam			0.149 **	0.062	0.138 **	0.064
Sample size	396		396		351	
Adjusted R squared	0.259		0.311		0.204	

Note: 1. Standard error in parenthesis is clustered at village level. 2. All regressions include village fixed effects. 3. The unit of observations for the regression is the plot. 4. Analysis is weighted by household level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Figure 1.

(a) Technology A



(b) Technology B

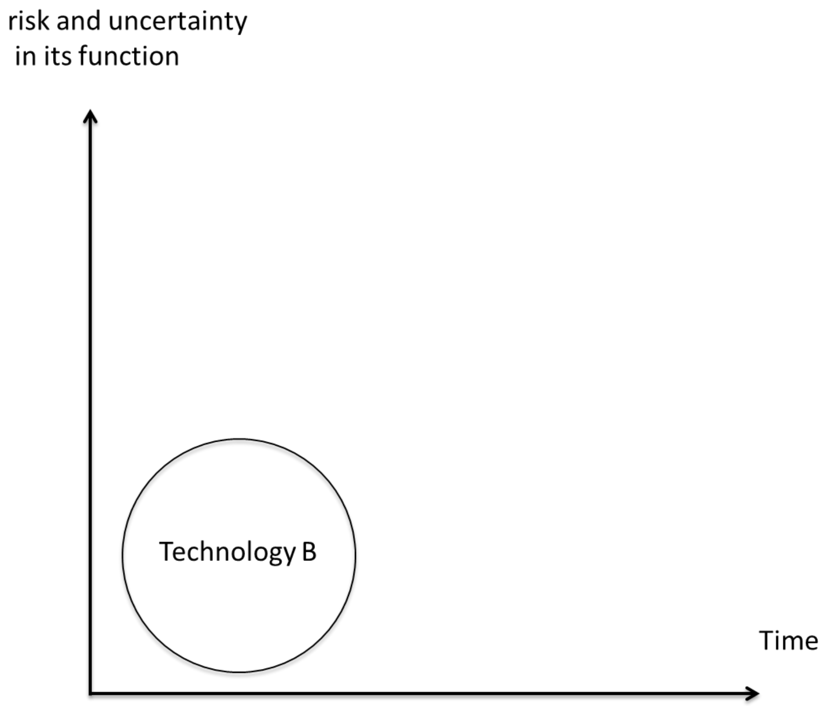


Figure 2. Photo of moisture meter