THE ROLE OF RISK, AMBIGUITY, AND TIME PREFERENCES IN THE PARTICIPATION IN RENEWABLE ENERGY PES PROGRAMS: EXPERIMENTAL EVIDENCE FROM CHINA

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Abstract

Using renewable energy sources to substitute for traditional energy materials such as firewood can reduce CO2 emissions and deforestation. This paper explores the role that risk, ambiguity, and time preferences play in the participation in renewable energy Payments for environmental services (PES) programs, and uses as a rural biogas program supported by government bond funds in China a case study. The most recent experimental methods are employed in the field to elicit the preference parameters. We find that (i) risk preferences affect farmers' participation in the biogas PES program, while ambiguity and time preferences have insignificant effects; (ii) farmers who are more risk averse are less likely to participate in the biogas program; (iii) the effect of risk preferences is significant only for impatient people, suggesting an interaction of risk and time preferences. We confirm the validation of the latest laboratory experimental methods, and the stability of laboratory experimental findings in the field. In addition, we go beyond expected utility theory by testing prospect theory in the field. Our findings support expected utility theory rather than prospect theory, suggest that people make rational choices and have tiny present bias, and that the utility function for certainty and uncertainty may be different.

Keywords: risk preferences, ambiguity preferences, time preferences, technology adoption, payments for environmental services, biogas

JEL Codes: D03, D81, Q54, Q55, Q57

1. Introduction

Despite China's rapid economic development over the last 30 years, people in rural China still depend heavily on firewood for cooking and heating that may cause deforestation (Zhang et al., 2009). Using renewable energy sources such as biogas to substitute for firewood is helpful in reducing deforestation and CO2 emissions (Katuwal and Bohara, 2009). The initial costs of using renewable energy sources are higher than the costs of using firewood, and farmers are often unable or unwilling to afford them. The Chinese government seeks to encourage farmers to adopt renewable energies through payments for environmental services (PES), which are economic instruments that use financial incentives to encourage environmental protection behaviours (Engel et al., 2008). A key factor for a successful PES program is the enrolment of a sufficient number of participants (Pagiola et al., 2008). Therefore, it is important to understand what factors influence participation in PES programs. Studies on PES programs in different countries suggest that household and individual characteristics such as farm size, household size, household income, age, education, individuals' attitudes towards programs and knowledge of the program are all important determinants of participation in PES programs (Chen et al., 2009; Mullan and Kontoleon, 2012; Pagiola et al., 2008; Wossink and Van Wenum, 2003; Zbinden and Lee, 2005).[1] However, to the best of our knowledge, there is currently no empirical evidence pertaining to the role of risk, ambiguity, and time preferences in the participation in existing PES programs. In this paper, we aim to fill in this gap by combining survey data with field experiments.

The role of risk, ambiguity, and time preferences regarding participation in PES programs is important for several reasons. First, to receive payments, participants in PES programs are usually required to enact a number of changes in their practices, such as altering

[1]These studies refer to the following PES programs: the Sloping Land Conversion Program in China (Chen et al., 2009; Mullan and Kontoleon, 2012), the Payment for Environmental Services program in Costa Rica (Zbinden and Lee, 2005), the Ecosystem Management Project in Nicaragua (Pagiola et al., 2008), and the Biodiversity Conservation Program in Germany (Wossink and Van Wenum, 2003).

their land use, or adopting conservation agriculture management techniques or renewable energy technologies. These activities can generate risks (e.g., decrease crop yields) (Graff-Zivin and Lipper, 2008), but even if the new technologies are no riskier than the current ones, individuals may perceive risks based on their own beliefs (Liu, 2013). Theoretical modelling of participation in PES programs has suggested that risk preferences should affect individuals' participation decisions (Graff-Zivin and Lipper, 2008). Second, ambiguity may affect the extent of participation in these programs because information about the program or the technologies could be lacking, or because of uncertain benefits (Ross et al., 2010). Previous studies have rarely distinguished risk and ambiguity preferences in their analyses. Risk refers to measurable uncertainty where probabilities of the outcomes are known, while ambiguity refers to uncertainty with unknown probabilities of outcomes (Ellsberg, 1961). Because of this disparity, it is necessary to separately examine risk and ambiguity preferences. Finally, in some cases participants in PES programs may be required to undertake initial investments themselves and recoup them later (Pagiola et al., 2008). This means that time preferences may play an important role in PES program participation (Graff-Zivin and Lipper, 2008).

As a case study, we examine a rural biogas program supported by government bond funds in China to investigate how risk, ambiguity, and time preferences affect farmers' participation in renewable energy PES programs. Using biogas to substitute for traditional energy materials such as firewood is helpful in reducing CO2 emissions and deforestation (Katuwal and Bohara, 2009). The biogas program is the largest renewable energy PES program in rural China. It receives an annual governmental investment of ¥2.5 billion and is being implemented throughout all provinces of Mainland China (MOA, 2007).[2] Participants of the program receive subsidies to build biogas pools, and they are responsible for using biogas in their daily lives. By 2010, there were 41 million households with biogas pools in China, accounting for 30% of suitable households (Feng et al., 2012; MOA, 2007), but there

[2] 1 US Dollar ≈ 6 Chinese Yuan

is still ample room for further biogas development. Investigating what determines participation in the program is a key step for the success of the program.

Previous studies that focused on the drivers of participation in PES programs used post-implementation data. However, post-implementation studies may suffer from reverse causality: the program may have affected participants' preferences and household and individual characteristics (e.g., income) leading to biased estimates of the effect of preferences on the program's participation. This study overcomes that issue by collecting survey data and conducting field experiments on households, that have not adopted the biogas pools yet.

This paper also contributes to the literature on technology adoption. Empirical studies on the relationship between technology adoption and risk, ambiguity, and time preferences are scarce, and are mainly related to farming technologies.[3] In previous studies, findings have been mixed. Yesuf and Köhlin (2009) find that risk and time preferences affect adopting new farming technologies, and field experiments conducted by Liu (2013) suggest that risk preferences are linked to the adoption of genetically modified cotton. However, recent studies show that ambiguity preferences, rather than risk preferences, influence the adoption of new crops (Barham et al., 2011; Ross et al., 2010; Warnick et al., 2011). More evidence is necessary to understand the role of preferences on technology adoption, and in particular, on renewable energy adoption.

In addition, previous studies have used the method developed by Coller and Williams (1999) to elicit time preferences, and the methods developed by Holt and Laury (2002), and Tanaka et al. (2010) to elicit risk preferences. Although these methods are popular, they have several limitations. In these methods, individuals are presented with several binary choice questions. In each question, individuals choose one out of two options. At first, individuals

[3] These farming technologies are related to new crops adoption, soil conservation and fertilizer use (Liu, 2013; Warnick, et al., 2011; Yesuf and Köhlin, 2009).

may choose one option, and then switch to the other option. These methods generate a preference interval parameter based on the switch question[4], making them highly inefficient, as only the switch question and the question before it are used to calculate the interval. Moreover, the method proposed by Coller and Williams (1999) estimates an upwards-bias discount factor as a result of the linear utility assumption (Andersen et al., 2008; Andreoni and Sprenger, 2012), and the method proposed by Holt and Laury (2002) estimates the utility parameter using only expected utility theory, while ignoring prospect theory (Kahneman and Tversky, 1979).

Our study addresses these limitations by employing two very recent experimental methods: the convex time budget (CTB) method (Andreoni et al., 2012; Andreoni and Sprenger, 2012) and the convex risk budget (CRB) method (Andreoni and Harbaugh, 2009). These methods have several advantages. They are highly efficient, as every choice question captures information about an individual's preferences. The CTB method allows for concavity of the utility function and estimates the discount factor and utility parameters at the same time. The CRB method allows experimental results to determine whether expected theory or prospect theory fits the data best, as Tanaka et al. (2010) does. However, compared to their method, the CRB method uses a smaller number of choice questions, and produces precise parameter estimates instead of an estimated interval.

We use survey data and data collected from field experiments applied to 375 households in the Hubei Province of China. We find that risk preferences affect farmers' participation in the biogas PES program, while ambiguity and time preferences have insignificant effects, even while controlling for the farmers' knowledge of the biogas program and including village fixed effects to account for village heterogeneity. In particular, more risk averse farmers are less likely to participate in the program. The effect of risk preferences

[4] The question in which individuals switch their choices is called "switch question".

is significant only for impatient farmers, suggesting an interaction of risk and time preferences.

In addition, this paper contributes to the literature on time and risk preference elicitations (Andreoni and Sprenger, 2012; Holt and Laury, 2002). We replicate in the field the latest experimental methods implemented in the lab with U.S. student (Andreoni and Harbaugh, 2009; Andreoni et al., 2012; Andreoni and Sprenger, 2012; Laury and Holt, 2008). Our field experiments confirm the findings of the laboratory experiments. We find that people make rational choices, but we do not find high levels of reflection effect, that is when the signs of outcomes are reversed from positive to negative (reflection around 0), the preferences are reversed from risk aversion for gains to risk loving for losses (Kahneman and Tversky, 1979). Experimental data supports the independence axiom of expected utility theory, and not the probability weighting of prospect theory, that is individuals use a probability weighting function to calculate the prospect of a risky outcome (Kahneman and Tversky, 1979). The value of the present bias parameter is estimated to be 0.98, indicating that the present bias is extremely small. We also compare the utility parameters elicited in the Holt and Laury (2002) and CTB experiments and find no correlation, which raises a question as to whether it is correct to assume that the utility function under certainty is equal to the one under uncertainty.

The paper is organized as follows. Section 2 describes the Chinese biogas program. Section 3 presents the model employed in this paper. Section 4 describes the field experiments used to elicit individuals' risk, ambiguity, and time preferences. Section 5 describes the sample selection and data. Section 6 presents the results. Section 7 provides a discussion of the results. Section 8 concludes.

2. Background: the Chinese biogas program

Biogas is a mixture of gases, 50%-70% of which is methane, produced through the methane fermentation process from materials such as animal manure and crop residues (Weiland, 2010). A biogas pool that produces biogas for small households, usually has a capacity of 6-8 m^3 and is connected with the toilet, the pigsty, and the kitchen (CRESP, 2008). Neutral PH and high temperature is favourable for biogas production (Rajendran et al., 2012).

As a renewable energy, biogas has several advantages. It can substitute for traditional energy materials, such as firewood, straw, and coal, for heating and lighting, and so may be helpful in reducing CO_2 emissions and protecting forest lands (Panwar et al., 2011). The use of biogas also contributes to reducing indoor air pollution and disease, and helping farmers save time and effort on firewood collection (Katuwal and Bohara, 2009). Finally, the biogas pool produces green fertilizers as by-products, and using green fertilizers can reduce the costs of chemical fertilizers and increase crop yields (Zheng et al., 2010). The central Chinese government launched a rural biogas PES program supported by government bond funds in 2003 to promote the development of biogas in rural China. The program receives an annual governmental investment of ¥2.5 billion and is being implemented throughout all the provinces of Mainland China. By 2010, there were 70% of suitable households having no biogas pool (Feng et al., 2012). This ample room for further biogas development makes it important to investigate what affects farmers' participation in the biogas program.

Building a biogas pool and its corresponding alteration to the toilet, the pigsty, and the kitchen has a rough cost of ¥3000. Participants in the biogas program receive subsidies to build biogas pools, and they are expected to use biogas in their daily lives. The amount of subsidies is ¥1200 for households in the north-western and north-eastern areas, ¥1000 for households in the south-western area, and ¥800 for households in other areas. The subsidies are not enough to cover the cost, and participants also need to invest money or labour in building biogas pools. Although using biogas can annually bring ¥4500 profits (MOA, 2007),

the benefits are not immediately obtained after the investment. Therefore, farmers' decisions on participation may be affected by their time preferences. Using biogas contains some risks such as explosions (Rashid et al., 2010), digester failure, and process failure (Weiland, 2010). Individual difference in risk preferences may influence farmers' decisions on participation in the biogas program. Sometimes farmers lack information on biogas, and this obstacle generates ambiguity (Salomon and Silva Lora, 2009). Thus, ambiguity preferences may also play a role in participation.

3. The Model

Let Y_i be a dummy variable indicating farmers' participation in the biogas program. The participation decision can be modelled as

$$Y_i = \begin{cases} 1 & \text{if } Y_i^* = X_i\beta + \varepsilon_i \\ 0 & \text{otherwise} \end{cases}$$

where Y_i* is a latent variable capturing the utility of farmer *i* from the participation choice. The household *i* will choose to participate in the biogas program (Y_i=1) if Y_i*>0, and not participate (Y_i=0) otherwise. X_i is a vector of independent variables representing the attributes of the individual and the household. Three key independent variables are risk, ambiguity, and time preference parameters. Based on the findings in prior studies, we expect that farmers who are more risk averse, more ambiguity averse, and more impatient are less likely to participate in the biogas program.

X_i also includes other factors relating to individual and household characteristics. Age is expected to be negatively linked to participation in the biogas program. Older farmers are often reluctant to change their behaviours, reducing the probability of participation (Jolejole et al., 2009; Langpap, 2004). The empirical evidence on the effect of gender on participation in PES programs is ambiguous (Barr et al., 2011; Pagiola et al., 2008). Farmer with a higher level of education are expected to be more likely to acquire and process information, handle

administrative tasks, and recognize the benefits of participation (Zbinden and Lee, 2005). Therefore, years of education are expected to have a positive effect on participation. If farmers work off-farm, they may have access to information about the biogas program and higher income. Thus, working off-farm is expected to positively influence participation in the program.

Household size and household income are found to be positively associated with participation in previous studies (Barr et al., 2011; Mullan and Kontoleon, 2012). The evidences on the effect of land area on the participation is mixed (Barr et al., 2011; Langpap, 2004; Zbinden and Lee, 2005).

Pig dung is a ain input into biogas production. Households without pigs can buy materials from other households. Therefore, raising pigs is expected to have a positive effect on participation. If a household use other renewable energies it decreases the demand of biogas. Experience with applying to governmental programs make farmers familiar with the process, and increases the probability of participation. Quantities of firewood/straw, coal and liquefied petroleum gas are expected to be positively linked to participation because they indicate a high energy demand and biogas is a substitute for these energy materials. Perceived ease of use and knowledge of new technologies were also found in previous studies to increase the probability of technology adoption (Arkesteijn and Oerlemans, 2005).

4. Experimental Design

We conducted several experiments with paper and pencil to elicit the risk, ambiguity, and time preferences of farmers. A brief introduction of these methods is given below. For the purpose of comparing field experiment results with laboratory experiment results, we closely followed the instructions used in the laboratory experiments, and adapted them to the field only to the degree necessary. Examples of experimental instructions used in the field experiments are provided in Appendix A.

4.1 Measuring time preferences with the convex time budget (CTB) method

In the method proposed by Coller and Williams (1999), subjects choose between earlier payments, c_t, and later payments, c_{t+k}, over multiple iterations. They may choose earlier payments in some iterations, and then switch to later payments in remaining iterations. The switch point generates an interval of the discount factor. Coller and Williams (1999) assume linear utility $u(c_t)=c_t$, leading to an upwards-biased discount factor (Andersen et al., 2008; Andreoni and Sprenger, 2012). To correct the bias, Andersen et al. (2008) conduct the method introduced by Holt and Laury (2002) on the same individuals to estimate their utility parameters, and use the utility parameters in the Coller and Williams (1999) experiment. However, whether it is appropriate to impose the utility parameter obtained in risk experiments on data from time experiments is still unknown (Andreoni and Sprenger, 2012). Andreoni and Sprenger (2012) go beyond these methods and propose the CTB method, allowing for concavity of the utility function and estimating discount factor and utility parameters at the same time.

In the CTB experiment, subjects choose a combination of earlier payments, c_t, and later payments, c_{t+k}, under the following budget constraint:

$$(1+r)c_t+c_{t+k}=m \qquad (1)$$

where $(1+r)$ is the experimental gross interest rate, and m is the experimental budget.

Subjects are assumed to choose the combination that maximises the utility:

$$U(c_t, c_{t+k})=c_t^{\alpha}+\beta\delta^k c_{t+k}^{\alpha} \qquad (2)$$

where α is the utility parameter, β is the present bias parameter, and δ is the discount factor parameter. We can estimate these parameters by solving the problem of maximizing (2) subject to (1).

The requirement of computers in CTB design makes it difficult to conduct CTB in the field (Andreoni et al., 2012). Andreoni et al. (2012) developed a simpler method, the modified CTB (mCTB), that can be conducted by paper and pencil in field experiments. In the mCTB

method, subjects choose one option out of six discrete options within a given budget for each row. The utility parameter α, the present bias parameter β, and the discount factor parameter δ are obtained by solving the following utility maximization problem:

$$\max \ U(c_t, c_{t+k}) = c_t^{\alpha} + \beta\delta^k c_{t+k}^{\alpha}$$

$$\text{s.t.}(c_t, c_{t+k}) \in \left\{ \left(\frac{m}{1+r}, 0\right), \left(\frac{4}{5}\frac{m}{1+r}, \frac{m}{5}\right), \left(\frac{3}{5}\frac{m}{1+r}, \frac{2m}{5}\right), \left(\frac{2}{5}\frac{m}{1+r}, \frac{3m}{5}\right), \left(\frac{1}{5}\frac{m}{1+r}, \frac{4m}{5}\right), (0, m) \right\}$$

In the field experiment, we set the budget *m* as ¥50. Following Andreoni et al. (2012), four tables were used with four combinations of earlier and later days: today and 5 weeks from today, today and 9 weeks from today, 5 weeks and 10 weeks from today, 5 weeks and 14 weeks from today. In tables with delay lengths of 5 weeks, the price ratio, $(1+r)$, in each row was 1.05, 1.11, 1.18, 1.25, 1.43 and 1.82 (see Table A1 for an example). In tables with delay lengths of 9 weeks, $(1+r)$ was 1.00, 1.05, 1.18, 1.33, 1.67 and 2.22.

In the laboratory experiment, Andreoni and Sprenger (2012) adopt several methods to ensure the equivalence of the credibility and transaction costs of earlier and later payments. In their procedure, students receive both earlier and later payments in the form of a personal check via credible campus mailboxes. Two equal thank-you payments are separately added to earlier and later payments. In this way, subjects are forced to pick up their payments twice, no matter what choices they have made, in case they choose either all earlier payments or all later payments. Earlier and later payments are put into two envelopes with the addresses, payment amounts and dates written on them by the subjects themselves. This ensures they do not have to spend any extra effort to remember the information about their later payments. Moreover, this approach ensures correct information is printed on the envelopes.

In adapting the experiment to the field, some changes were necessary. Cash, instead of checks, was used as payment method. After the survey, subjects were invited to check the amount being paid to them. Once they were certain the amount was correct, the subjects divided the earlier payments and later payments into two envelopes. We sealed the envelopes

in front of them, and wrote down the payment dates on the envelopes. Turning their backs to us, they wrote down their names on the sealed envelopes themselves, and put the envelopes into a bag so as to protect their anonymity. Before leaving, we gave the bag containing all the envelopes to a trusted person (usually the village head). On the day they were to receive the payments, the trusted person delivered the envelopes to the subjects' houses. Although this set-up differs in a number of ways from the laboratory experiments, the field experiments followed the same spirit and tried to keep as close as possible to the original set-up. Interviews with the subjects also show that they were confident of the payment delivery.

4.2 Measuring risk preferences with the convex risk budget (CRB) method

Andreoni and Harbaugh (2009) propose a new method to measure risk preferences, the CRB method. Similar to the CTB method, with the CRB method subjects choose a combination of outcomes *x* and probabilities *p* under a budget *m*:

$$r_1 p + r_2 x = m \tag{3}$$

where r_1 is the price of the probability *p*, r_2 is the price of the outcome *x*, and *m* is the experimental budget.

Subjects are assumed to choose the combination that maximises the utility:

$$U(p,x) = px^{\alpha} \tag{4}$$

where α is the utility parameter indicating risk preferences. We can estimate the risk preference parameter by solving the problem of maximizing (4) subject to (3).

In the laboratory experiment, the outcome *x* and the corresponding probability *p* are shown on a computer screen. In the field experiment, we simplified the CRB method in the mode of the mCTB method (Andreoni et al., 2012). In each row, 5 discrete options under a given budget were presented. Each option was a combination of the outcome *x* and the probability *p* such that

$$(x,p)\in\left\{\left(\frac{5}{6}\frac{m}{r_1},\frac{1}{6}\frac{m}{r_2}\right),\left(\frac{4}{6}\frac{m}{r_1},\frac{2}{6}\frac{m}{r_2}\right),\left(\frac{3}{6}\frac{m}{r_1},\frac{3}{6}\frac{m}{r_2}\right),\left(\frac{2}{6}\frac{m}{r_1},\frac{4}{6}\frac{m}{r_2}\right),\left(\frac{1}{6}\frac{m}{r_1},\frac{5}{6}\frac{m}{r_2}\right)\right\}$$

Following Andreoni and Harbaugh (2009), the set of (r_1, r_2, m) was (12.5, 1, 12), (18.75, 1, 12), (37.5, 1, 12), (75, 1, 12), (150, 1, 12), (25, 1, 24), (37.5, 1, 24), (75, 1, 24), (150, 1, 24) (see Table A2 for an example).

4.3 Measuring ambiguity preferences

Based on Ellsberg's two-colour problem (Ellsberg, 1961), Lauriola and Levin (2001) develop the ambiguity game to elicit ambiguity preferences independently from risk preferences. A subject is presented with 41 choice questions. In each question, subjects choose one out of two options, called option1 and option2. Both options have two outcomes: receiving a payment or nothing. Subjects know the probabilities of the outcomes in option1, but do not know them for option2. The probabilities for option1 change in steps (Δp=0.025). In our field experiment, we set the change of probability in the unambiguity option as Δp=0.1 to make a shorter list, as in the design of the field experiment conducted in Laos by Ross et al. (2010). We used a table containing 11 rows of options (see Table A3 for an example). From row 1 to row 11, the probability of receiving ¥10 in option1 increased while the probability in option2 remained unknown.

Kahn and Sarin (1988) propose a model to analyse individuals' choices under ambiguity. When the probability of outcomes is unknown, people perceive the probability as following:

$$w(E)=\bar{p}-\lambda\sigma$$

Where E is the event that the subject receives payments, $w(E)$ is the perceived probability of event E, p is the actual probability of event E, $\bar{p}$ is the average probability of p, σ is the standard deviation of p, λ is the parameter representing ambiguity preferences ($\lambda>0$ means ambiguity aversion, $\lambda=0$ means ambiguity neutral, $\lambda<0$ means ambiguity loving).

In our ambiguity game, the distribution of p in the ambiguity option is a uniform distribution between 0 and 1, so $\bar{p}$ equals 0.5 and σ equals $1/\sqrt{12}$. The row at which the subjects switch their choices generates an interval for ambiguity parameter λ. For instance, a subject switches from the ambiguity option to the risk option in the third row. This suggests that the subject prefers the ambiguity option when p equals 0.1 in the risk option, and prefers the risk option when p equals 0.2. Then we can obtain the following inequalities:

$$0.1<0.5-\sqrt{12}\lambda$$

$$0.2>0.5-\sqrt{12}\lambda$$

Therefore we can obtain $\lambda \in (0.087, 0.115)$, and we take the mid-point as the estimation of ambiguity parameter.

In the field experiments described above, payments were decided by the subject's choice in one particular row of each experiment. At the end of the field experiment session, the subjects chose one person to randomly pick one number that would decide the row. Then they sent other people to randomly pick one number and so decide the probability of option2 in the ambiguity game, as well as the outcomes in the risk and ambiguity experiments. The subjects' earnings depended on respondents' choices and chances. The highest earning could be up to ¥100, which was roughly twice the daily wage of the subjects. After finishing the survey, the respondents were invited to another room, one person at a time, to receive their earnings. The order of experiments was randomised to control for order effects.

5. Sample Selection and Data Description

We conducted a survey and the above described field experiments in Shayang county of the Hubei Province in March and April of 2012 to investigate the determinants of participation in the rural biogas program. The area was selected because of suitable geographical and climatic conditions for biogas, and the existing heterogeneity among households in participation in the

biogas program. We first conducted a pilot survey and field experiments to test whether farmers understood the questionnaire and the experimental instructions. Based on their feedback, we revised the design and conducted another pilot field work. We then conducted the final survey and field experiments. [5] The survey and field experiments were anonymous. Each respondent was assigned an identification number.

We randomly selected twelve villages to participate in the survey and field experiments. In these villages, among 3549 households with no biogas pool, 97 households had just applied for the biogas program[6]. We selected all these 97 households, and randomly selected 350 households from the remaining 3452 households that did not apply for the biogas program. The village leader helped us inform the decision-maker of each household and persuade him/her to participate in the field work. There were 375 respondents participating in both the survey and the field experiments, generating a response rate of 84%. In the analysis, 10 observations were dropped because the households already started to build the biogas pools, 11 observations were dropped because of missing data on household and individual characteristics[7], 2 observations were dropped because their choices in the CTB experiment have no variation, and 32 observations were dropped because they did not have a unique switch point in the ambiguity game. Thus, the sample size was 320 in the analysis.

In our sample,. 22% of households have just applied for the program but have not built biogas pools yet, 36% plan to apply and 42% do not plan to apply. One issue is whether it is appropriate to group the households which have applied and those which plan to apply together. We test the effects of individual and household characteristics, risk, ambiguity and time preferences on group differences. Table B1 in appendix B shows that only land area has a significant effect. However, land area has an insignificant effect on participation, regardless

[5] The final sample excluded villages where we conducted the pilot field work.
[6] These households submitted the application forms from the end of 2011 to the day when we started the field work.
[7] Two observations have missing data on land area, three observations have missing data on household income, one observation has missing data on perceived ease of use of biogas, three observations have missing data on knowledge of biogas, two observations have missing data on energy consumption.

of combing households which have applied and plan to apply or only using households which have applied for the program (see Table B2). Therefore, both groups are analysed together, yielding a larger sample size.

Figure 1 shows the distribution of risk, ambiguity, and time preferences. Approximately 40% of farmers are risk averse and 60% are ambiguity averse. Farmers' daily discount factor parameters vary from below 0.97 to above 1.01, which implies that people vary from being impatient to being patient. The correlation between the risk preference parameter elicited in the CRB experiment and the ambiguity preference parameter is weak (correlation coefficient ρ=-0.103, p-value=0.067).

[insert Figure 1 about here]

Table 1 displays the descriptive statistics for the other independent variables used in the analysis. On average, the respondents are 48 years old and have completed a middle school education (9 years). There are more male decision-makers (76%) than female decision-makers (24%). About half of the respondents work off-farm for some months in the last year, think that biogas will be easy to use, and have good knowledge of biogas. The average household has 5 persons, land of 0.7 hectare, and an annual income of ¥24,000, and annually consumes 551 kilograms of firewood and straws, 261 balls of coal, and 4 tanks of liquefied petroleum gas. Roughly half of the households use other renewable energies (e.g., a solar water heater), have applied for other renewable energy programs, and raise pigs which provide the materials of biogas.

[insert Table 1 about here]

6. Results

In this section, we first present the role of risk, ambiguity, and time preferences in the participation in the biogas program, and then we compare our results obtained with Chinese farmers with those of previous studies that used laboratory experiments with U.S. students to elicit risk, ambiguity, and time preferences.

6.1. Determinants of participation in the biogas program

Table 2 presents the coefficient estimates of a probit model on the marginal effects of household and individual characteristics, and risk, ambiguity, and time preferences on participation in the biogas program. The standard errors are clustered at the village level. We put the parameters of risk preferences, ambiguity preferences, and time preferences into model 1, model 2, and model 3 respectively. Only the risk preference parameter has a significant effect at the 5% significance level. As expected, people who are more risk averse are less likely to participate in the program. Age, education, household income, having other renewable energy sources, having applied to other renewable energy programs, and perceived ease of use also have significant effects. If a household has a higher household income, has applied other renewable energy programs before, but has no other renewable energy source, and has an older, more educated decision-maker who thinks it will be easy to use biogas, then the likelihood of participation is higher. In column 4, we put risk, ambiguity, and time preferences together into the model; the results are stable. In column 5, we further control for village heterogeneity by including village fixed effects. The magnitude of the marginal effect of risk preferences slightly increases from 0.012 to 0.013, and the significance level decreases from the 5% level to the 10% level. The village fixed effects also make the effect of education become insignificant, but lead to a significant effect of gender at the 10% level, indicating that being male increases the likelihood of participation.

[insert Table 2 about here]

Column 1 and column 2 of Table 3 explore whether the effects of risk and ambiguity preferences on participation differ between impatient and patient people respectively. We define as impatient people with discount factors below or equivalent to the median and as patient people with discount factors above the median. We find that ambiguity preferences are insignificant for both impatient and patient farmers while risk preferences only matter for impatient people. Compared with the results on the full sample, the magnitude and significance of the marginal effect of risk preferences increase to 0.056 and 1% significance level respectively. This suggest an interaction of risk and time preferences. In column 3 and column 4 of Table 3, we separately estimate the effect of ambiguity preferences for people with good knowledge and poor knowledge of biogas. Results show that ambiguity preferences are insignificant for both types.

[insert Table 3 about here]

We can test whether these different effects in the subpopulation are significant by estimating a model that includes the interaction terms (see Table C1 in Appendix C). However, for nonlinear models, simply examining the coefficient of the interaction term can lead to misleading conclusions, and a graphical presentation of the effects is more informative (Ai and Norton, 2003; Greene, 2010; Norton et al., 2004). We compute the interaction effects for each observation by following Norton et al. (2004). Figure 2 shows the interaction effects between risk preferences and time preferences, ambiguity preferences and time preferences, and ambiguity preferences and knowledge in the first, second, and third row respectively. In the figure, the left graphs plot both incorrect (red lines) and correct (blue dots) interaction effects. Z-statistics of the interaction effects are plotted in the graphs on the right. Reference

lines at +/- 1.65 in the right graphs generate an interval of statistical significance, that is the inside of the interval indicates insignificance and the outside refers to significance at the 10% level. For most observations, the interaction effects of risk preferences and time preferences are significant, while ambiguity preferences do not have significant interaction effects with time preferences and knowledge. These results confirm the findings in Table 3. [8]

[insert Figure 2 about here]

The findings that risk preferences, rather than ambiguity preferences, are significantly linked to participation contrast with Warnick et al. (2011). One reason could be that ambiguity preferences only matter when people lack information. Yet we find that ambiguity preferences have insignificant effects for people with good and poor knowledge of biogas. However, the indicator of good or poor knowledge is generated based on farmers' answers to three questions on biogas, and it may not reveal the true extent to which people know the biogas technology. Another reason could be that previous studies focus on new crop adoption, but we focus on renewable energy technology adoption, which may be affected by risk and ambiguity preferences in different ways. The effect of time preferences is also insignificant. This may be caused by the diverse ways in which farmers invest in building biogas pools. Farmers can invest either money or labour. When they invest their labour, they may not realize a non-monetary cost and thus time preferences do not matter.

6.2. Comparisons between field and laboratory experiments

In this section, we compare the results we obtained in the field experiments with Chinese farmers with results from previous laboratory experiments conducted with U.S. students. We

[8] We also investigate whether the effects of risk, ambiguity, and time preferences are different for men and women, and for poor and rich households. We find no significant interaction effect. See Appendix C for details.

analyse five key questions regarding people's behaviour: (i) whether or not people are affected by present bias, (ii) whether utility parameters over certainty and uncertainty are the same, (iii) whether people make rational choices in experiments, (iv) whether the independence axiom holds or whether probability weighting holds, and (v) whether an effect indicating a high level of reflection exists.

Present bias. In CTB laboratory experiments, the present bias parameter, β, is estimated and tested whether it differs from 1 (Andreoni et al., 2012; Andreoni and Sprenger, 2012). If β equals 1, there is no present bias. In contrast, if β is smaller than 1, it indicates present bias. Present bias parameters in our field experiment are estimated to be 0.98. As in laboratory experiments, the null hypothesis that β equals 1 is rejected (p-value=0.043), but the value of β is very close to 1. This indicates that even if there is present bias, the present bias is extremely small.

Utility over certainty and uncertainty. Andreoni and Sprenger (2012) conduct both the CTB and Holt and Laury (2002) laboratory experiments and compare utility parameters obtained in these two experiments. They find no correlation between the two utility parameters. In our field experiments, we also find that the two utility parameters are not significantly correlated (correlation coefficient ρ=0.062, p-value=0.277).This finding raises the question of whether or not it is appropriate to impose the utility parameter obtained in risk experiments to data of time experiments (Andersen et al., 2008; Andreoni and Sprenger, 2012).

Andreoni and Sprenger (2010) argue that the utility is functionally discontinued over certainty and uncertainty. This could explain the lack of correlation between the CTB and Holt and Laury (2002) utility parameters, that the CTB method measures utility over certainty while the Holt and Laury (2002) method elicits utility over uncertainty. The argument is further supported by our experimental data: the utility parameter estimated in the CRB method, which only involved risk, is also not correlated with the CTB utility parameter

(correlation coefficient ρ=-0.001, p-value=0.982), but is correlated with the HL utility parameter (correlation coefficient ρ=0.164, p-value=0.004).

Rational choices. Andreoni and Harbaugh (2009) investigate whether people make rational choices in CRB by calculating the violations of the Generalized Axiom of Revealed Preference (GARP), using methods developed by Varian (1982). The left graph of Figure 3 shows choices under a budget constraint. If the dot *a* is chosen when the dot *a* and the dot *b* are both available, we say that *a* is directly revealed as preferred to *b*, written *a*D*b*. If *b* is within the budget set (presented as *b'* in the graph), we say that *a* is strictly directly revealed as preferred to *b*, written *a*S*b*. If there is a chain connecting *a* to *z* such that *a*D*b*, *b*D*c*, …, *y*D*z*, we say that *a* is revealed as preferred to *z*, written *a*P*z*. GARP states that if *a*P*b*, then *b*S*a* will never happen. The right graph of Figure 3 displays a violation of GARP. Under budget 2, *a* is revealed as preferred to *b*. However *b* is strictly directly revealed as preferred to *a* under budget 1, indicating a violation of GARP.

[insert Figure 3 about here]

In the laboratory experiment, 85% of subjects (75 students) have no more than two violations of GARP in the CRB gains experiment, suggesting general coherence to rational choice. In our field experiment, 98% of subjects (312 farmers) have no GARP violation, highly supporting the model of rational choice.

The independence axiom vs. probability weighting. The independence axiom is the basic assumption of expected utility theory, while the alternative, probability weighting, is an important part of prospect theory (Kahneman and Tversky, 1979). For an outcome *x* with probability *p*, the independence axiom assumes that the utility of the outcome is $pu(x)$. Probability weighting, however, suggests that the utility is $w(p)u(x)$, where $w(p)$ is the probability weighting function. The offer curve, drawn based on choices over budgets with

the same constraint *m*, should be vertical under the independence axiom and downward sloping under probability weighting, as shown in Figure 4 (Andreoni and Harbaugh, 2009).

[insert Figure 4 about here]

In the laboratory experiment conducted by Andreoni and Harbaugh (2009), the independence axiom is supported by the results, which show that of all the offer curves, 78% are vertical and only 1% are downward sloping. We obtain similar results in our field experiments: 86% of the offer curves are vertical and 4% are downward sloping.

Andreoni and Harbaugh (2009) also test the statistical and economic significance of the independence axiom. We follow their methods and obtain similar results (Table 4 and Table 5). The slopes of offer curves are significant and negative, rejecting both the independence axiom and probability weighting. The small elasticity, however, suggests incomplete rejection of the independence axiom. When compared with probability weighting, the independence axiom is more supported by both laboratory and field experiments.

[insert Table 4 about here]

[insert Table 5 about here]

The reflection effect. Prospect theory suggests the presence of the reflection effect, i.e., when the signs of outcomes are reversed from positive to negative (reflection around 0), the preferences are reversed form risk aversion for gains to risk loving for losses (Kahneman and Tversky, 1979). In contrast to the high level of reflection effect in prospect theory, parallel gains/losses in the laboratory experiments conducted by Laury and Holt (2008) show a low level of reflection effect (less than 13% when used with real monetary payoffs). In our

parallel gains/losses in the Holt and Laury (2002) field experiments, 31% of subjects have a reflection effect.

7. Robustness checks and sensitivity analysis

Although risk, ambiguity, and time preferences are theoretically assumed exogenous, they may be endogenous in empirical applications because preference parameters are estimated based on subjects' choices instead of direct observations (Warnick et al., 2011). Our results do not have endogeneity problems caused by ex-post measurements, but they may suffer from omitted variables which are both correlated with preferences and with participation. We conduct a generalized sensitivity analysis to assess the omitted variable bias (Harada, 2012; Imbens, 2003). Figure 5 presents a threshold (the blue line) showing how large omitted variables should be to halve the effect of risk preferences. The graph also shows two independent variables that are closest to the threshold. None of the two independent variables exceeds the threshold, which indicates that it is very unlikely to having unobservable variables that could halve the effect of risk preferences. Therefore, even if there is endogeneity caused by omitted variables, it is unlikely to have a major effect on results.

[insert Figure 5 about here]

A second potential concern is missing data. We dropped 45 observations due to missing data, accounting for 12% of the respondents. Are the results stable if we include these observations in the analysis? We impute missing data using the approach proposed by Royston (2005). The results estimated with and without the imputed are similar (see Table 6), which supports the robustness of our results.

[insert Table 6 about here]

8. Conclusions

Renewable energy sources have the potential to reduce CO_2 emissions and deforestation through substituting for traditional energy materials such as firewood (Panwar et al., 2011). Payments for environmental services (PES) are used to promote renewable energy technology adoption. Understanding what factors affect participation is important for a successful PES program. In this study, we investigate the effects of risk, ambiguity, and time preferences on farmers' participation in a renewable energy PES program, the rural biogas program in China. We combine survey data with field experiments by implementing the latest experimental methods conducted in the lab with U.S. students (Andreoni and Harbaugh, 2009; Andreoni et al., 2012; Andreoni and Sprenger, 2012; Laury and Holt, 2008). We find that risk aversion decreases the likelihood to participate in the biogas program, and it affects, in particular, impatient people. Impatient people with an one unit higher risk preference parameter are 6% less likely to participate. Ambiguity and time preferences have insignificant effects on participation.

In addition, we find that a household which has a higher household income, has applied to other renewable energy programs before, but has no other renewable energy source, and has an older, more educated decision-maker who thinks it will be easy to use biogas is more likely to participate in the biogas program.

This study also provides an important contribution to the literature on preference elicitation by providing external validity to the latest laboratory experimental methods from the U.S. (Andreoni and Harbaugh, 2009; Andreoni et al., 2012; Andreoni and Sprenger, 2012; Laury and Holt, 2008). Our field experiments confirm the findings of the laboratory experiments. We find that people are rational when they make choices in experiments. In addition, the experimental data supports the independence axiom of expected utility theory, but rejects the assumption of probability weighting and the high level of reflection effect in prospect theory. In addition, we find evidence of only a very small present bias in the

experiments eliciting time preferences, and the utility function under certainty and uncertainty may be different.

The findings of this study have useful implications. For policy-makers, the distinction between risk and ambiguity preferences can be helpful for designing policies. If risk preferences are significant, policies that help farmers reduce their perceived risk should be implemented (e.g., minimising the risks of new technologies, organising risk management training, designing a particular kind of insurance). If ambiguity preferences are the key factors, policy-makers should make efforts to deliver more information about the technology and programs to farmers in order to reduce ambiguity. For the Chinese biogas program, policies targeting risk need to be designed and implemented to increase participation rates.

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Figure 1. Distributions of time, risk, and ambiguity preference parameters

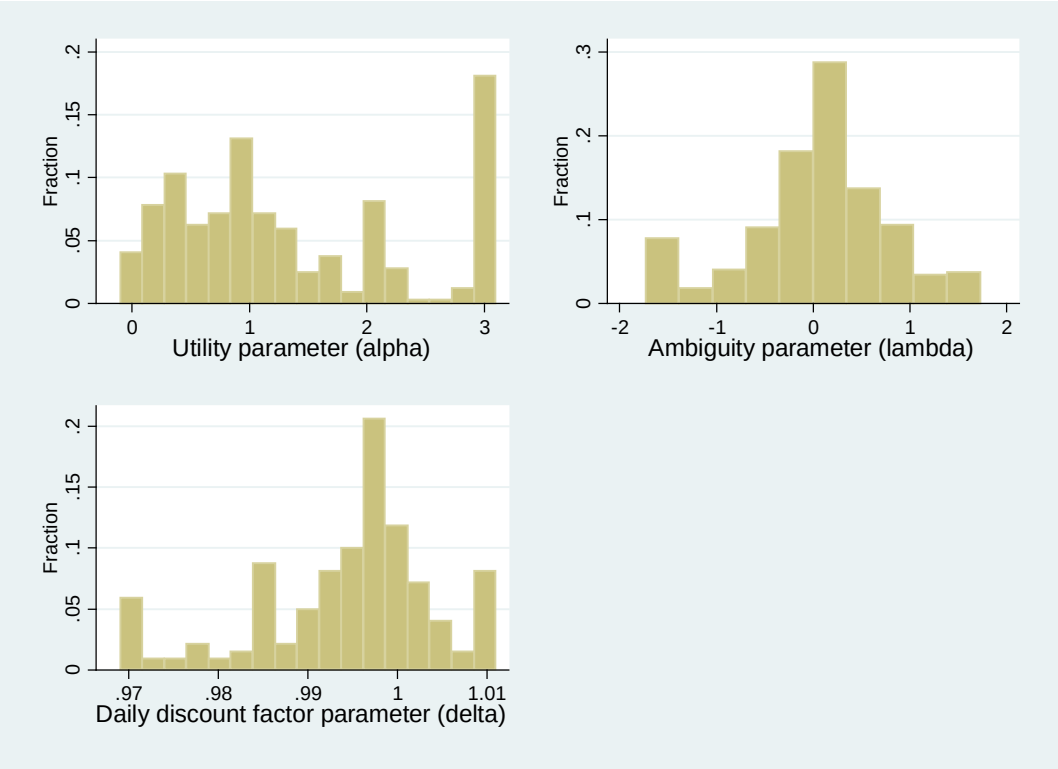


Table 1. Descriptive statistics of household and individual characteristics

Variables	Description	Mean	Std. Dev.
age	Age of respondent (in years)	47.587	8.900
gender	=1 if gender of respondent is male, 0 otherwise	0.762	0.426
education	Education in years	9.047	2.205
work off- farm	=1 if respondent worked off-farm for some months in the last year, 0 otherwise	0.522	0.500
household size	Household size	4.519	1.369
land	Land area (hectare)	0.665	0.311
income	Annual income of the household (1000 Yuan)	24.271	15.845
other energy	=1 if household has other renewable energies (e.g., solar water heater), 0 otherwise	0.516	0.501
other applications	=1 if household applied to other renewable energy programs, 0 otherwise	0.459	0.499
pigs	=1 if household has pigs, 0 otherwise	0.425	0.495
firewood/straw	Quantity of firewood/straw (100 kg)	5.512	12.736
coal	Quantity of coal (100 ball)	2.612	5.356
lpg	Quantity of liquefied petroleum gas (LPG) (tank)	4.022	2.454
easy use	=1if agreed with the statement “the biogas will be easy to use”, 0 otherwise	0.613	0.488
knowledge	=1 if has good knowledge of biogas technology, 0 otherwise	0.541	0.499

Table 2. Marginal effects of risk, ambiguity, and time preferences on participation in the biogas program

	(1)	(2)	(3)	(4)	(5)
risk	0.012**			0.012**	0.013*
	(0.005)			(0.005)	(0.007)
ambiguity		-0.020		-0.011	0.008
		(0.034)		(0.035)	(0.039)
time			-0.665	-0.580	-0.676
			(0.892)	(0.911)	(1.078)
age	-0.008***	-0.008**	-0.008**	-0.008***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
gender	0.124	0.124	0.120	0.127	0.207*
	(0.097)	(0.103)	(0.098)	(0.100)	(0.110)
education	0.030**	0.031**	0.030**	0.031**	0.022
	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)
work off- farm	0.002	0.003	0.004	0.003	0.010
	(0.058)	(0.058)	(0.058)	(0.059)	(0.065)
household size	-0.019	-0.021	-0.022	-0.019	-0.023
	(0.030)	(0.030)	(0.031)	(0.031)	(0.031)
land	-0.052	-0.040	-0.051	-0.056	-0.029
	(0.102)	(0.099)	(0.104)	(0.106)	(0.106)
income	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
other energy	-0.272**	-0.239**	-0.241**	-0.272***	-0.331***
	(0.101)	(0.106)	(0.105)	(0.100)	(0.097)
other applications	0.225**	0.205*	0.207*	0.226**	0.249**
	(0.105)	(0.104)	(0.105)	(0.104)	(0.112)
pigs	0.061	0.060	0.059	0.059	0.036
	(0.076)	(0.076)	(0.078)	(0.076)	(0.082)
firewood/straw	-0.001	-0.000	-0.000	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
coal	0.006	0.006	0.006	0.006	0.004
	(0.007)	(0.008)	(0.008)	(0.007)	(0.006)
lpg	0.020	0.020	0.021	0.021	0.025
	(0.016)	(0.015)	(0.016)	(0.016)	(0.021)
easy use	0.399***	0.386***	0.385***	0.398***	0.399***
	(0.061)	(0.065)	(0.065)	(0.061)	(0.067)
knowledge	0.084	0.072	0.077	0.086	0.100
	(0.058)	(0.055)	(0.057)	(0.055)	(0.063)
Village fixed effect	No	No	No	No	Yes
Observations	320	320	320	320	320
Log Likelihood	-176.46	-178.28	-178.23	-176.31	-164.80
Pseudo-R^2	0.190	0.182	0.182	0.191	0.244

Note: Marginal effects at the mean are reported. Standard errors clustered at the village level are in parentheses.

* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 3. Marginal effects of risk preferences, and ambiguity preferences on participation in the biogas program (subpopulation)

	(1) Impatient (discount factor <=median)	(2) Patient (discount factor >median)	(3) Good knowledge	(4) Poor knowledge
risk	0.056***	0.008		
	(0.021)	(0.005)		
ambiguity	0.013	-0.022	0.095	-0.006
	(0.040)	(0.054)	(0.061)	(0.068)
Household and individual characteristics [a]	Yes	Yes	Yes	Yes
Other preferences [b]	Yes	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes	Yes
Observations	155	160	169	140
Log Likelihood	-71.59	-73.78	-70.68	-72.41
Pseudo-R^2	0.330	0.315	0.370	0.254

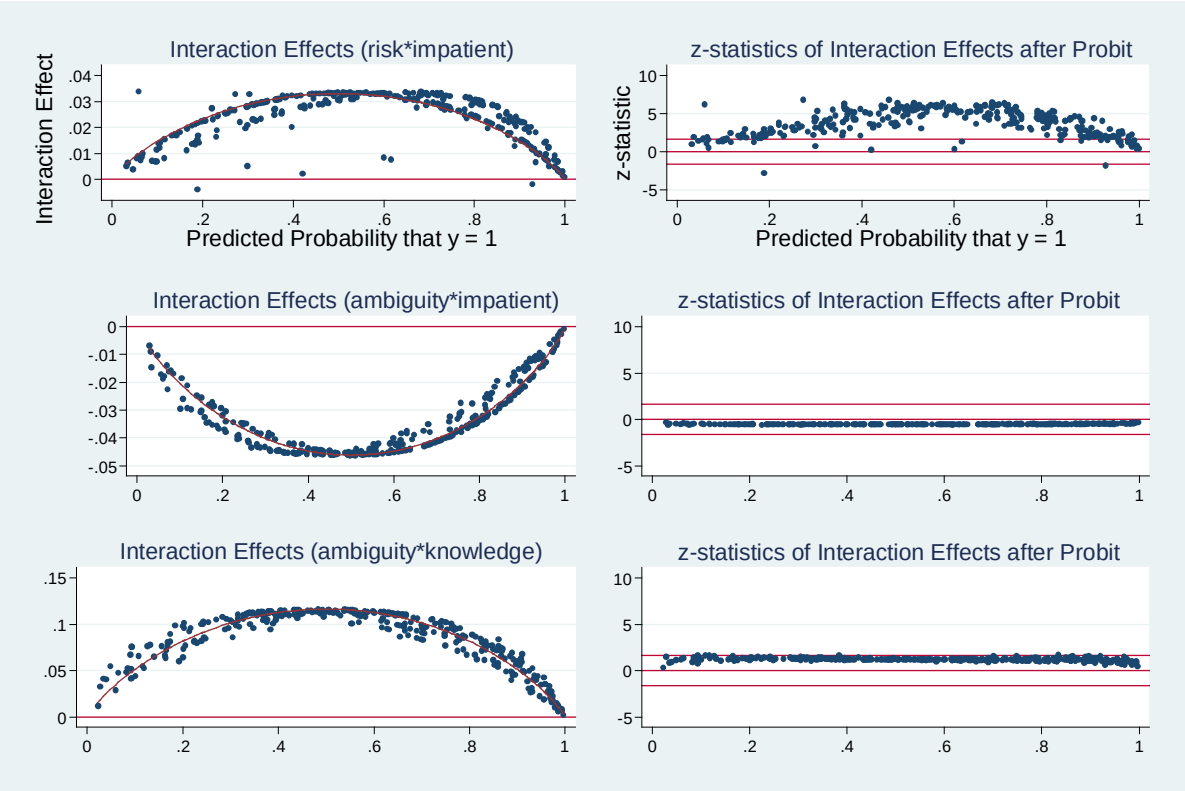
Note: Marginal effects at the mean are reported. Standard errors clustered at the village level are in parentheses.

* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

[a] Household and individual characteristics include age, gender, and education years of the decision maker, whether the decision maker works off farm, household size, land area, household income, whether the household has other renewable energy sources, has applied to other renewable energy programs, and raises pigs, quantity of firewood/straw, coal, and liquefied petroleum gas consumed by the household, whether the decision maker thinks it will be easy to use biogas and has good knowledge of biogas.

[b] Risk preferences and time preferences.

Figure 2. Interaction effects



Note: In right graphs, reference lines are z=±1.65, representing significance levels of 10%.

Figure 3. GARP and the violation of GARP

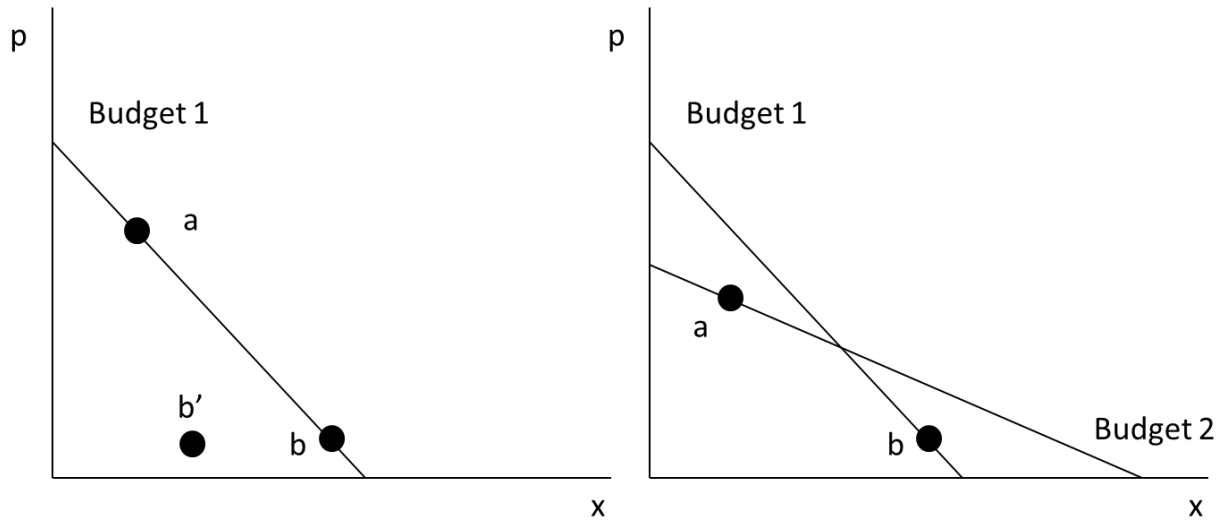
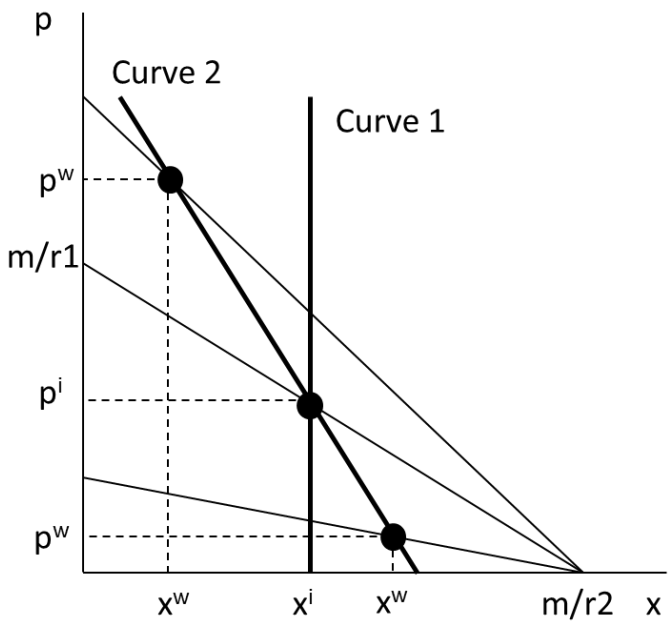


Figure 4. Offer curves



Note: Source: Adapted from Andreoni and Harbaugh (2009).

Table 4. Test of the slope of offer curves

	(1)	(2)	(3)
r’	-0.530***		
	(0.117)		
(m’=12)*r’		-0.306***	
		(0.106)	
(m’=24)*r’			-0.830***
			(0.243)
m’=12	-6.364***	-6.114***	-6.890***
	(0.162)	(0.170)	(0.228)
Constant	13.259***	12.878***	13.475***
	(0.224)	(0.208)	(0.270)
Observations	2850	2850	2850
R^2	0.409	0.407	0.410

Note: Standard errors clustered at the individual level are in parentheses.
* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.
Andreoni and Harbaugh (2009) test the slope of the offer curves by regressing the outcome *x* on the relative price $r'=r_1/r_2$ of the probability *p* with fixed effects for real income $m'=m/r_2$.

Table 5. Economic significance of offer curves

Real income, $m'=m/r_2$	m’=12	m’=24
Real price of probability p, r_1/r_2		
Maximum	1.5	1.5
Minimum	0.125	0.25
Percent change	1100%	500%
Mean choice of outcome x		
At maximum price	6.42	12.28
At minimum price	7.05	13.50
Percent change	-9%	-9%
Comparisons		
Diff. of mean x, t-test	0.63***	1.29***
Gross elasticity, $(\Delta x/x)/(\Delta p/p)$	-0.008	-0.018

Note: * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Figure 5. Sensitivity analysis

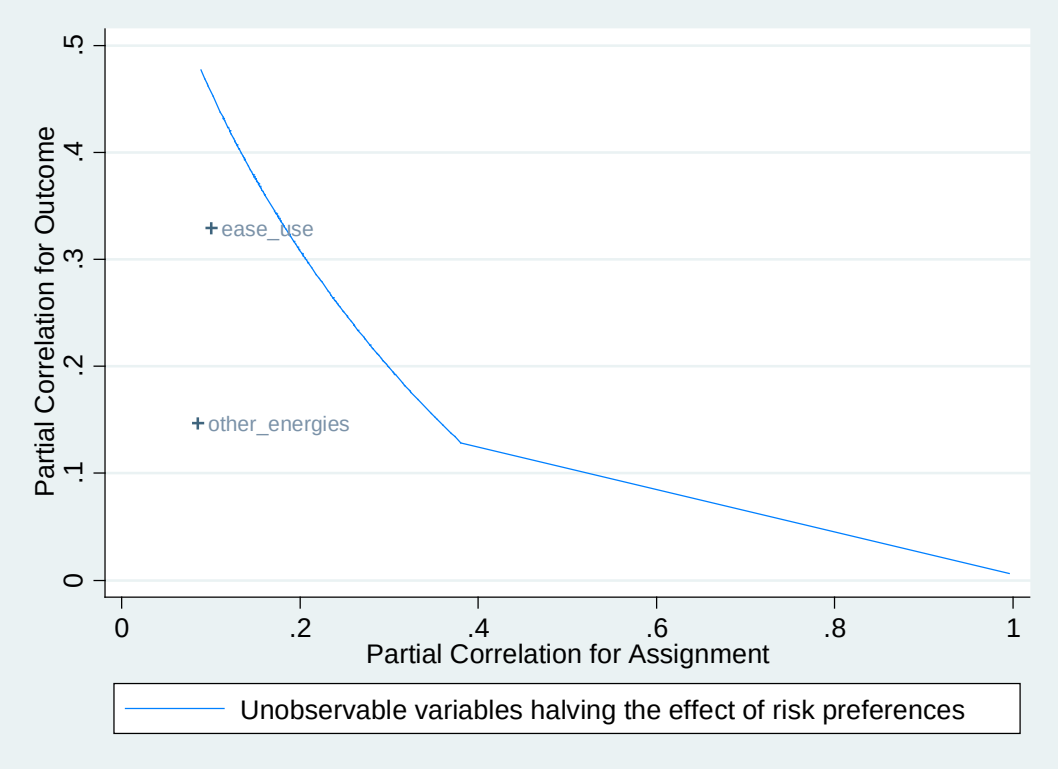


Table 6. Comparisons between non-imputed and imputed data

	(1) Non-imputed	(2) Imputed
risk	0.033*	0.030*
	(0.017)	(0.017)
ambiguity	0.021	0.087
	(0.103)	(0.119)
time	-1.760	-1.178
	(2.809)	(2.757)
age	-0.025***	-0.025***
	(0.009)	(0.006)
gender	0.531*	0.449
	(0.283)	(0.282)
education	0.057	0.012
	(0.036)	(0.032)
work off- farm	0.026	0.088
	(0.169)	(0.155)
household size	-0.059	-0.036
	(0.080)	(0.070)
land	-0.076	-0.004
	(0.276)	(0.257)
income	0.016***	0.015***
	(0.006)	(0.006)
other energies	-0.892***	-0.530***
	(0.279)	(0.183)
other applications	0.665**	0.417*
	(0.310)	(0.214)
pigs	0.095	0.128
	(0.216)	(0.194)
firewood/straw	-0.002	0.002
	(0.010)	(0.010)
coal	0.010	0.002
	(0.016)	(0.017)
lpg	0.066	0.061
	(0.056)	(0.055)
easy use	1.060***	0.970***
	(0.192)	(0.144)
knowledge	0.260	0.249**
	(0.166)	(0.118)
Village fixed effect	Yes	Yes
Observations	320	365
Log Likelihood	-164.80	-
Pseudo-R^2	0.244	-

Note: The probit coefficients are reported.
Standard errors clustered at the village level are in parentheses.
* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Appendix A. Examples of forms used in the field experiments

Table A1. The CTB method

TODAY and 5 WEEKS from today							
For each decision number (1 to 6) below, decide the AMOUNTS you would like for sure today AND in 5 weeks by checking the corresponding box. Example: In decision 1, if you wanted ¥47.5 today and ¥0.0 in 5 weeks you would check the left-most box. Remember to check only one box per decision!							
1	payment TODAY	¥47.5	¥38.0	¥28.5	¥19.0	¥9.5	¥0.0
	and payment in 5 WEEKS	¥0.0	¥10.0	¥20.0	¥30.0	¥40.0	¥50.0
		□	□	□	□	□	□
2	payment TODAY	¥45.0	¥36.0	¥27.0	¥18.0	¥9.0	¥0.0
	and payment in 5 WEEKS	¥0.0	¥10.0	¥20.0	¥30.0	¥40.0	¥50.0
		□	□	□	□	□	□
3	payment TODAY	¥42.5	¥34.0	¥25.5	¥17.0	¥8.5	¥0.0
	and payment in 5 WEEKS	¥0.0	¥10.0	¥20.0	¥30.0	¥40.0	¥50.0
		□	□	□	□	□	□
4	payment TODAY	¥40.0	¥32.0	¥24.0	¥16.0	¥8.0	¥0.0
	and payment in 5 WEEKS	¥0.0	¥10.0	¥20.0	¥30.0	¥40.0	¥50.0
		□	□	□	□	□	□
5	payment TODAY	¥35.0	¥28.0	¥21.0	¥14.0	¥7.0	¥0.0
	and payment in 5 WEEKS	¥0.0	¥10.0	¥20.0	¥30.0	¥40.0	¥50.0
		□	□	□	□	□	□
6	payment TODAY	¥27.5	¥22.0	¥16.5	¥11.0	¥5.5	¥0.0
	and payment in 5 WEEKS	¥0.0	¥10.0	¥20.0	¥30.0	¥40.0	¥50.0
		□	□	□	□	□	□

Table A2. The CRB method

Gains (receive money)						
For each decision number (1 to 9) below, decide the option you **like most** by checking the corresponding box. Example: In decision 1, if the option you like most is: 16 out of 100 chance of gaining ¥10, you would check the left-most box. Remember to check only one box per decision!						
1	__out of 100 chance of gaining	16 ¥10 □	32 ¥8 □	48 ¥6 □	64 ¥4 □	80 ¥2 □
2	__out of 100 chance of gaining	11 ¥10 □	21 ¥8 □	32 ¥6 □	43 ¥4 □	53 ¥2 □
3	__out of 100 chance of gaining	5 ¥10 □	11 ¥8 □	16 ¥6 □	21 ¥4 □	27 ¥2 □
4	__out of 100 chance of gaining	3 ¥10 □	5 ¥8 □	8 ¥6 □	11 ¥4 □	13 ¥2 □
5	__out of 100 chance of gaining	1 ¥10 □	3 ¥8 □	4 ¥6 □	5 ¥4 □	7 ¥2 □
6	__out of 100 chance of gaining	16 ¥20 □	32 ¥16 □	48 ¥12 □	64 ¥8 □	80 ¥4 □
7	__out of 100 chance of gaining	11 ¥20 □	21 ¥16 □	32 ¥12 □	43 ¥8 □	53 ¥4 □
8	__out of 100 chance of gaining	5 ¥20 □	11 ¥16 □	16 ¥12 □	21 ¥8 □	27 ¥4 □
9	__out of 100 chance of gaining	3 ¥20 □	5 ¥16 □	8 ¥12 □	11 ¥8 □	13 ¥4 □

Table A3. The ambiguity game

Gains (receive money)													
For each decision number (1 to 11) below, decide the option you **like most** by checking the corresponding box. Example: In decision 1, if you like option 2 most you would check the right-most box. Remember to check only one box per decision!													
	Option 1							Option 2					
		If the number reads	You receive	and	If the number reads	You receive			If the number reads	You receive	and	If the number reads	You receive
1	□	-	¥10		1-10	¥0		□	?	¥10		?	¥0
2	□	1	¥10		2-10	¥0		□	?	¥10		?	¥0
3	□	1-2	¥10		3-10	¥0		□	?	¥10		?	¥0
4	□	1-3	¥10		4-10	¥0		□	?	¥10		?	¥0
5	□	1-4	¥10		5-10	¥0		□	?	¥10		?	¥0
6	□	1-5	¥10		6-10	¥0		□	?	¥10		?	¥0
7	□	1-6	¥10		7-10	¥0		□	?	¥10		?	¥0
8	□	1-7	¥10		8-10	¥0		□	?	¥10		?	¥0
9	□	1-8	¥10		9-10	¥0		□	?	¥10		?	¥0
10	□	1-9	¥10		10	¥0		□	?	¥10		?	¥0
11	□	1-10	¥10		-	¥0		□	?	¥10		?	¥0

Appendix B. Group differences between households that have applied and households that plan to apply for the biogas program

Table B1. Marginal effects of individual and household characteristics on applying for the biogas program

Probit model	Marginal effects
age	-0.000
	(0.005)
gender	0.026
	(0.095)
education	0.005
	(0.021)
work off- farm	-0.043
	(0.081)
household size	-0.008
	(0.031)
land	-0.252*
	(0.141)
income	-0.003
	(0.003)
other energy	-0.066
	(0.149)
other applications	0.081
	(0.149)
pigs	0.043
	(0.083)
firewood/straw	-0.006
	(0.005)
coal	-0.001
	(0.007)
lpg	0.002
	(0.015)
easy use	-0.096
	(0.093)
knowledge	-0.016
	(0.077)
risk	-0.020
	(0.039)
ambiguity	0.077
	(0.052)
time	-3.891
	(3.756)
Observations	185
Log Likelihood	-115.48
Pseudo-R^2	0.059

Note: The dependent variable is whether apply for the program (=1 if have applied; =0 if plan to apply). Marginal effects at the mean are reported. Standard errors clustered at the village level are in parentheses.
* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table B2. Marginal effects of land and firewood/straw on participation in the biogas program

	Full sample		Restricted sample	
	(1)	(2)	(3)	(4)
land	-0.044	-0.010	-0.136	-0.077
	(0.101)	(0.101)	(0.104)	(0.065)
Other characteristics [a]	Yes	Yes	Yes	Yes
Village fixed effect	No	Yes	No	Yes
Observations	320	320	205	205
Log Likelihood	-178.40	-166.91	-109.74	-86.68
Pseudo-R^2	0.181	0.234	0.166	0.341

Note: Households that plan to apply for the biogas program are excluded in the restricted sample. Marginal effects at the mean are reported. Standard errors clustered at the village level are in parentheses.

[a] Other characteristics include age, gender, and education years of the decision maker, whether the decision maker works off farm, household size, household income, whether the household has other renewable energy sources, has applied to other renewable energy programs, and raises pigs, quantity of firewood/straw, coal, and liquefied petroleum gas consumed by the household, whether the decision maker thinks it will be easy to use biogas and has good knowledge of biogas.

Appendix C. Interaction effects

Table C1. Marginal effects of interaction terms

	(1)	(2)	(3)
risk	0.006		
	(0.005)		
risk*impatient [a]	0.032***		
	(0.006)		
ambiguity		0.034	-0.048
		(0.059)	(0.073)
ambiguity*impatient		-0.044	
		(0.081)	
impatient	-0.155*	-0.092	
	(0.084)	(0.080)	
ambiguity*knowledge			0.112
			(0.091)
knowledge			0.093
			(0.064)
Household and individual characteristics [b]	Yes	Yes	Yes
Other preferences	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes
Observations	320	320	320
Log Likelihood	-162.20	-163.85	-164.04
Pseudo-R^2	0.256	0.248	0.247

Note: Marginal effects at the mean are reported. Standard errors clustered at the village level are in parentheses.
* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.
[a] Impatient=1 if discount factor<=median
[b] Household and individual characteristics include age, gender, and education years of the decision maker, whether the decision maker works off farm, household size, land area, household income, whether the household has other renewable energy sources, has applied to other renewable energy programs, and raises pigs, quantity of firewood/straw, coal, and liquefied petroleum gas consumed by the household, whether the decision maker thinks it will be easy to use biogas and has good knowledge of biogas.

Table C2. Marginal effects of risk, ambiguity, and time preferences on participation in the biogas program (subpopulation)

	(1) Male	(2) Female	(3) Poor (income <=median)	(4) Rich (income >median)
risk	0.011**	0.024	0.012**	0.025*
	(0.005)	(0.021)	(0.006)	(0.015)
ambiguity	0.020	-0.058	-0.020	0.013
	(0.055)	(0.133)	(0.033)	(0.100)
time	-0.462	-4.285	0.074	-1.862
	(1.395)	(5.229)	(1.654)	(2.022)
Household and individual characteristics [a]	Yes	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes	Yes
Observations	237	75	196	116
Log Likelihood	-112.55	-31.49	-98.07	-53.58
Pseudo-R^2	0.293	0.390	0.278	0.283

Note: Marginal effects at the mean are reported. Standard errors clustered at the village level are in parentheses.

* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

[a] Household and individual characteristics include age, gender, and education years of the decision maker, whether the decision maker works off farm, household size, land area, household income, whether the household has other renewable energy sources, has applied to other renewable energy programs, and raises pigs, quantity of firewood/straw, coal, and liquefied petroleum gas consumed by the household, whether the decision maker thinks it will be easy to use biogas and has good knowledge of biogas.

Table C3. Marginal effects of interaction terms

	(1)	(2)	(3)	(4)	(5)	(6)
risk	0.020	0.013*	0.013*	0.025*	0.013*	0.013*
	(0.013)	(0.007)	(0.007)	(0.013)	(0.007)	(0.007)
ambiguity	0.010	0.014	0.009	0.002	0.015	0.005
	(0.040)	(0.038)	(0.039)	(0.041)	(0.092)	(0.042)
time	-0.702	-0.674	-2.805*	-0.700	-0.706	-1.668
	(1.086)	(1.079)	(1.694)	(1.111)	(1.116)	(1.416)
risk*gender	-0.010					
	(0.014)					
ambiguity*gender		-0.009				
		(0.081)				
time*gender			2.749			
			(2.204)			
gender	0.230**	0.207*	-0.900			
	(0.100)	(0.109)	(0.237)			
risk*poor				-0.016		
				(0.013)		
ambiguity*poor					-0.019	
					(0.092)	
time*poor						1.926
						(2.206)
poor [a]				-0.088	-0.117	-0.962
				(0.097)	(0.088)	(0.186)
Household and individual characteristics [b]	Yes	Yes	Yes	Yes	Yes	Yes
Other preferences	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	320	320	320	320	320	320
Log Likelihood	-164.66	-164.80	-164.35	-166.36	-166.79	-166.52
Pseudo-R^2	0.244	0.244	0.246	0.236	0.234	0.236

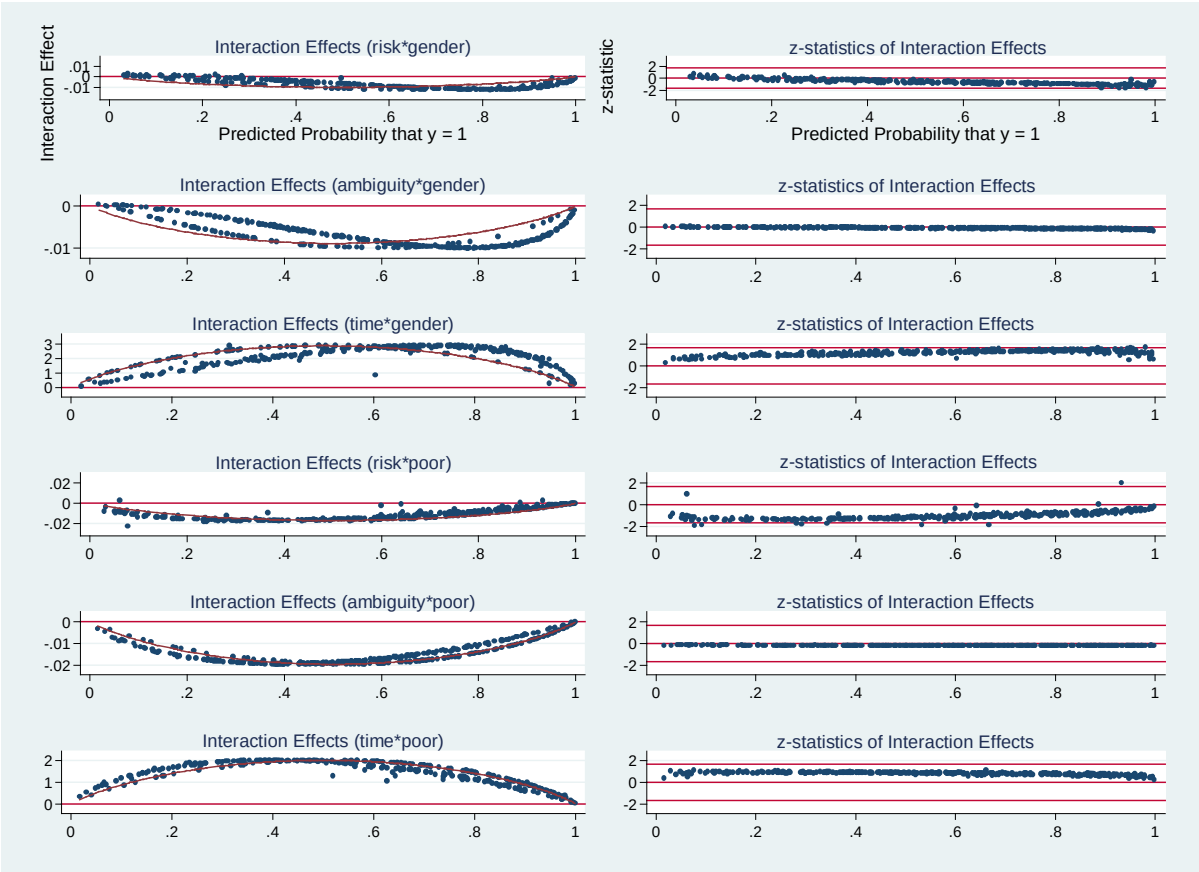
Note: Marginal effects at the mean are reported. Standard errors clustered at the village level are in parentheses.

* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

[a] Poor=1 if income<=median

[b] Household and individual characteristics include age, gender, and education years of the decision maker, whether the decision maker works off farm, household size, land area, household income, whether the household has other renewable energy sources, has applied to other renewable energy programs, and raises pigs, quantity of firewood/straw, coal, and liquefied petroleum gas consumed by the household, whether the decision maker thinks it will be easy to use biogas and has good knowledge of biogas.

Figure C1. Interaction effects with gender and poor



Note: In right graphs, reference lines are z=±1.65, representing significance levels of 10%.