Social Exchanges, Attitudes toward Uncertainty and Technology Adoption by Bangladeshi Farmers: Experimental Evidence

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Abstract

The literature discusses risk aversion as one of the behavioral determinants of technology adoption. However, little attention has been paid to measuring ambiguity aversion of poor people in developing countries or in finding the role of ambiguity aversion in technology adoption. Risk experiments in the previous studies have been designed in such a way that individuals face the risky and/or ambiguous situations alone. Individuals in the real world, especially farmers in developing countries, are likely to get information from peers before making any decision regarding a new innovation that has an ambiguous nature. This paper addresses two broad issues. The first issue is to measure the risk and ambiguity preferences of Bangladeshi rural farmers. The paper investigates whether the attitudes toward uncertainty (risk and ambiguity) differ when farmers face the uncertainty alone versus when they are allowed to communicate with peer groups of 3 or 6. It also investigates whether farmers' demographic characteristics affect their attitudes toward uncertainty or not. A second issue is to find whether a farmer's ambiguity aversion is important in explaining technology adoption decisions. Combining measured behavioral variables from the experimental data with a household survey data, the study provides two conclusions. First, Bangladeshi farmers in the sample are mostly risk and ambiguity averse. Their risk and ambiguity aversion, moreover, differ when they face the uncertain prospects alone from when they can communicate with other peer farmers before making decisions. The study also finds that farmer's demographic characteristics affect both risk and ambiguity aversion. Second, and perhaps more importantly, findings from the study suggest that the roles of risk and ambiguity aversion on technology adoption depend on which measure of uncertainty behavior is incorporated in the adoption model. While risk aversion increases the likelihood of technology adoption when farmers face uncertainty alone, only ambiguity aversion matters and it reduces the likelihood of technology adoption when farmers face uncertainty in groups of three. Neither risk aversion nor ambiguity aversion matter when farmers face uncertainty in groups of six.

Key Words: Ellsberg paradox, uncertainty, risk, ambiguity, technology adoption, expected utility theory, prospect theory, experimental economics.
JEL Classification Numbers: C91, C92, C93, D81, O13, O33, Q16.

1. INTRODUCTION

The literature on technology adoption demonstrates that individuals' attitudes toward uncertainty are an important factor in technology adoption decisions, including agricultural technologies. Risk aversion is among the important factors determining technology adoption (Srinivasan, 1972; Feder, 1980; Feder *et al*., 1985; Liu, 2013; Ward and Singh, 2014; Barham *et al*., 2013; Alpizar *et al*., 2011). Another type of uncertainty that is less studied is ambiguity aversion. Ambiguity aversion implies that an agent has a preference for a known risk over an unknown risk. The literature also demonstrates the changes in attitudes toward uncertainty when subjects are allowed to communicate among themselves before making choices over risky and ambiguous prospects in the experiments (Alpizar *et al*., 2011; Engle *et al*., 2013). The outcome of a new technology, whether good or bad, or the distribution of its outcome is unknown to the agent. The benefits or the distribution of benefits of the status quo, the existing practices, may contain a risk component but the risk is known to the agent from the past. Hence, adoption of a new agricultural technology contains an unknown risk

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(ambiguity), thereby giving rise to the issue of the role of ambiguity aversion in technology adoption. The current study measures the coefficients of risk and ambiguity aversion of Bangladesh farmers using data from a series of experiments. In order to investigate whether attitudes change due to communications, subjects were allowed to communicate in groups of 3 and 6 before making choices over uncertain prospects. Combining the measured attributes from the experimental data with a survey data, the study estimates a discrete choice model of technology adoption in order to investigate the effects of attitudes toward uncertainty (risk aversion and ambiguity aversion) on technology adoption in different situations: facing uncertainty alone, in groups of 3, and 6.

It is expected that an ambiguity-averse agent will not adopt a new technology as readily as an ambiguity neutral agent. However, it remains unclear whether the attitudes toward risk and ambiguity work in the indicated direction (Barham *et al*., 2013). Empirical questions regarding risk and ambiguity have important policy implications. In the case of risk-aversion, policy makers have focused to date on helping to improve *ex-post* risk coping mechanisms such as farmers' access to formal credit and insurance markets. On the other hand, in the case of ambiguity aversion, policy makers can help via *ex-ante* mechanisms to reduce farmers' uncertainty or perceived uncertainty through education, agricultural research, technical assistance or agricultural extension services (Engle-Warnick *et al*., 2011). Therefore, because of the different policy prescriptions for the two cases, it is important to know the relative importance of the two behavioral effects in order to guide policies toward eliminating any negative effects of uncertainty on the rural poor. The literature also discusses farmers' capacity and willingness to coordinate in pursuit of lower adoption costs. Sometimes, the behavior of others (mostly peers, neighbors, or people in the same network in different dimensions) influence own decisions (Jackson, 2014) including technology adoption decision for two reasons. First, agents (farmers) learn from observing decisions and experiences of others or communicating with others in their network (Banerjee, 1992; Bandiera and Rasul, 2006; Conley and Udry, 2010; Besley and Case, 1997; Engle *et al*. 2013; Jackson, 2014), namely social learning (Munshi, 2008). Second, because of economies of scope, the costs and benefits of technology adoption are potentially a function of how many people adopt it (Dybvig and Spatt, 1986). Therefore, it is important to examine whether communication among farmers changes attitudes toward uncertainty and hence technology adoption.

Like most experiments measuring risk and ambiguity, this study is a version of the Ellsberg's two-color urn experiment. The study investigates two broad issues. First, it attempts to measure the risk preferences of Bangladeshi farmers to test the degree to which they are risk and/or ambiguity averse. By allowing communication among subjects in different size groups of 3 and 6 in the experiments, the study also investigates whether farmers' attitudes remain the same when they face uncertainty alone versus in a group, as well as whether group size matters with respect to attitudes toward uncertainty. The existence of coordination in social exchanges and its effect on farmers' attitudes (Bandiera and Rasul, 2006; Besley and Case, 1997; Engle et al. 2013) is addressed in the latter part. The study also attempts to identify, through regression analysis, whether demographic characteristics have any effects on attitudes toward uncertainty.

This study addresses a second issue – whether farmers' measured attributes have any effect on adoption of integrated pest management (IPM) practices in Bangladesh. The main focus, however, is given on the effect of ambiguity aversion on technology choice. The study finds that Bangladeshi farmers in the sample are generally risk and ambiguity averse. However, their risk and ambiguity aversion as well as the distribution of the measured attributes (of both risk and ambiguity aversion) differ when they face uncertain prospects alone versus when they are able to communicate with other peer farmers before making decisions. Farmers exhibit preferences toward the two extreme behaviors when faced with uncertainty in groups of 3 rather than when they face it alone or in groups of 6. While considering the effects of demographic characteristics on the attitudes, household size increases the likelihood of extreme risk aversion, but decreases ambiguity aversion which is robust to different measures of risk aversion. The number of dependents in the household increases ambiguity aversion, and being married reduces it. Second, and perhaps more importantly, the study finds that the roles of risk and ambiguity aversion in technology adoption depend on which measure of uncertainty is incorporated in the adoption model. When risk and ambiguity preferences that were measured when subjects faced the uncertainty alone are used in the adoption model, only risk aversion appeared to affect the technology choice. Using those measured parameters when subjects faced uncertainty in groups of 3, ambiguity aversion reduced technology adoption. The behavioral variables have no effects on technology choice when those were measured from experiments when subjects faced uncertainty in groups of 6.

The rest of the paper is organized as follows. Section 2 presents a review of the literature measuring risk preferences in developing countries and provides a brief review of determinants of agricultural technology adoption. Section 3 provides the context of the study and the data. Section 4 discusses the experimental design and procedure, while section 5 discusses the results. Section 6 presents conclusions and directions for further research.

2. Literature Review

Studies on technology adoption mostly center on a wide range of issues such as farm size (Feder *et al*., 1985; Weil, 1970), land tenurial arrangements (Bardhan, 1979; Feder, 1980); education (Foster and Rosenweig, 1996; Huffman, 2001; Foltz, 2003), social stature such as membership in associations (Sidibe, 2005; Ben Yishay and Mobarak, 2014), information constraints (Fischer and Lindner, 1980; Schutjer and Van der Veen, 1977; Burton *et al*., 2003; Alcon *et al*., 2011), credit constraints (Weil, 1970; Lowdermilk, 1972; Lipton, 1976; Feder and Umali, 1993), Social learning and social networks (Foster and Rosenweig, 1995; Conley and Udry, 2010; Bandiera and Rasul, 2006; Duflo *et al*., 2008), and risk (Srinivasan, 1972; Feder, 1980; Feder *et al*., 1985; Liu, 2013; Ward and Singh, 2014). Feder *et al*., (1985) in their survey of technology adoption literature mentioned risk aversion as one of the major factors hindering the adoption of new technologies.

Sandmo (1971), Srinivasan (1972), and Feder (1980) are among the early studies taking risk preferences into consideration in the analysis of technology choices in theoretical settings. Excluding risk preferences in an empirical study potentially produces bias in the estimated effects of other determinants. As a remedial measure of this bias, it has been challenge to measure the risk preferences and incorporate that measured risk into the analysis of technology adoption. Studies in the literature focusing on risk preferences differ in methods for data collection and include analyses based on experimental lotteries as well as the analysis of production decisions based on data collected from household surveys. Binswanger (1980, 1981) was among the first experimental researchers to measure risk aversion of farmers in developing countries. Among studies in experimental lotteries, some have been based on hypothetical lotteries (Hill, 2009; de Brauw and Eozenou, 2014), some on real lotteries (Miayata, 2003; Wik *et. al*., 2004; Liu, 2013; Yesuf and Bluffstone, 2009; Tanaka *et al*., 2010; Harrison *et al*., 2010), and some on the both (Binswanger, 1981; Holt and Lary, 2002; Mosley and Verschoor, 2005). Moreover, the conceptual framework found in the literature on characterizing risk preferences varies from expected utility theory (EUT) to prospect theory (PT).

There are variations in experimental designs in the studies in order to measure attitudes toward uncertainty. The designs vary from lotteries holding outcome probabilities constant and varying payouts (Binswanger, 1980, 1981; Miayata, 2003; Barr, 2003; Wik *et al*., 2004) to a multiple price list (MPL) approach where probabilities vary holding payouts constant (Holt and Laury, 2002; Eckel *et al*., 2002; Harrison *et al*., 2005; Harbaugh *et al*., 2002). In the MPL approach, participants are shown certain lottery pairs at once (i.e., on a sheet or computer screen, similar to Table A1 in the appendix, and are asked to mark their preferences (lottery A or lottery B) in each row.

Though less common, studies to investigate attitudes toward ambiguity have been conducted using predominantly undergraduate student populations in developed countries. Experimental studies of attitudes toward ambiguity in farming societies in developing countries have begun but as of yet, few conclusions have been drawn. Among the few experimental studies of ambiguity attitudes of farming societies are Henrich and McElreath (2002), Akay *et al*., (2012), Ward and Singh (2014), and Engle-Warnick *et al*., (2011). Another strand of literature on measuring the attitudes toward uncertainty includes the presence of social exchanges in the experiments. The idea behind allowance of social exchanges among subjects is that agents coordinate among themselves in real world before making any decision. By doing so, they attempt to reduce any ambiguity as well as cost that is related to gathering information (Alpizar *et al*., 2011). Furthermore, social learning occurs while communicating with other agents (Munshi, 2008) that plays an important role in participatory development and contains the potential to build on and enhance social capital (Labonne and Chase, 2011; Engle *et al*., 2013).

Using a framed field experiment, Alpizar *et al*., (2011) estimated the risk and ambiguity preferences for coffee farmers in the Tarrazu region of Costa Rica. The region was heavily affected by tropical storm Alma in early 2008. Since this type of storm is new to the region, they related it to ambiguity and attempt to investigate the role of ambiguity aversion on the choice of adaptation due to climate change, i.e., this type of storm. Furthermore, they allowed subjects to communicate in some rounds to make the decision in order to explore the role of communication and opportunities for cost reduction due to economies of scope arising from full coordination on the decision to adapt or not to adapt to climate change. In an experimental study, Engle *et al*., (2013) examined the effect of participating in a social exchange on risk and ambiguity preferences. They conducted experiments in which participants made choices to reveal both their risk and ambiguity preferences. The subjects then participated in a social exchange of information, an unstructured online chat with other participants, and were again asked to make choices that reveal their risk and ambiguity preferences. The social exchange that is a way of social learning provided the basis for measuring the effects of social exchange on risk and ambiguity preferences. A separate group of subjects, the control group, viewed but did not participate in a past chat before they made their choices that revealed their risk and ambiguity preferences. They compared the latter two rounds of the experiments to measure the effects of participation in a social exchange on subjects' attitudes toward uncertainty. A limitation to their study, however, is that the set-up of social exchange in their experiments was online which is different from a face-to-face social exchange. This is more important when we consider the decision-making and social learning of farming societies in developing countries where virtual communication is not so common. Therefore, their study may not be generalizable to different groups of subjects.

Regardless of the conceptual framework (EUT vs. PT) and experimental approach, most studies found subjects in developing countries to be risk and ambiguity averse (Binswanger, 1980, 1981; Henrich and McElreath, 2002; Akay *et al*., 2011; Alpizar *et al*., 2011; Engle *et al*., 2013; Ward and Singh, 2014 among others.). Even though the communication among subjects reduced risk aversion (Engle *et al*., 2013), so far it has not reduced the ambiguity aversion (Alpizar *et al*., 2011; Engle *et al*., 2013). One reason for not improving the clarification about the ambiguous situation may be the form of communication such as online in Engle *et al*., (2013) or the reliability of the information provider in the period of communication. In that case, ambiguous situation may be improved by providing better information. More importantly, the information should be transferred by individuals who are well endowed with skills and reliable to the agents on the receiving end.

The literature on attitudes toward uncertainty is not limited to measuring the risk aversion and ambiguity aversion coefficients. Recent studies relate those measured behaviors to actual behaviors of technology adoption empirically (Engle-Warnick *et al*., 2007; Ward and Singh, 2013; Alpizar *et al*., 2011). The literature on the effects of estimated attitudes variables on technology choices appeared to have mixed results. While considering the role of the opportunity for cost reduction, Alpizar *et al*., (2011) found that the pursuit of cost reductions significantly increased the degree of adaptation. When communication was allowed, farmers were able to coordinate more frequently in pursuit of the reduced adaptation costs. However, when no financial motives were allowed, communication was found to be irrelevant to the farmer's private decision. Engle-Warnick *et al*., (2007) found that it is not risk aversion that influenced the choice of diversity among varieties of crops by Peruvian farmers but the ambiguity aversion that was influential. Coupling measured coefficients of risk, loss, and ambiguity aversion with a discrete choice model of technology adoption, Ward and Singh (2014) found that while ambiguity aversion was not stronger influential to choose a new innovation, risk and loss aversion increased the likelihood of switching to new, risk-reducing variety.

3. Context of the Experiment and the Data

Integrated pest management (IPM) is a way to combat pests while reducing the use of chemical inputs. It is growing in importance globally, especially in more developed countries, as a way to combat agricultural pests (Norton *et al*., 2005). With the support of the USAID-IPM Innovation Lab (IL), a randomized controlled trial (RCT) was begun in summer 2013 in four districts (Jessore, Magura, Barisal, and Jhalokathi) of Bangladesh in order to measure the impact of an agricultural technology information dissemination strategy on IPM adoption. First, a baseline household survey of 832 households was conducted. In order to elicit the farmers' risk attitudes, we asked 300 farmers in Jessore and Magura districts to participate in a behavioral field experiment. Farmers in Jessore and Magura districts were selected due to more availability of IPM practices in the region, compared to the other two districts, which is important for the second part of the study. Because those farmers were already in an RCT, it helped us to exploit socio-economic and pest-management practices data collected in the survey for further analysis. They were reached by the local extension workers and were given the option to participate or not. Of 300 farmers, 115 farmers in 15 villages in two districts: 48 farmers from 6 villages in Jessore and 67 farmers from 9 villages in Magura agreed to participate. 11 farmers were dropped after the experiment due to not completing the sessions. Using this pool of subjects in the behavioral experiment provides an additional opportunity to conduct a similar experiment with the same subjects in the following season to examine the dynamics of a farmers' attitudes toward uncertainty over time, and to compare their behavior based on different theories: expected utility theory and prospect theory.

4. Eliciting Risk and Ambiguity Preferences: Experimental Design and Procedure

The literature on risk elicitation procedures tend to follow either the pioneering work of Binswanger (1980) or that of Holt and Laury (2002). The differences between the two have been discussed in the previous section. Our instrument, presented in table A2-A3 in appendix, is different from the one employed by those authors. We follow the approach employed by Akay *et al*., (2012), Capon (2009), and Ross *et al*.,(2012) by asking respondents to directly compare certain amounts and lotteries. The design of the experiment is similar to a multiple price list (MPL), following Barham *et. al*., (2013) and Akay *et al*., (2012), which is a slightly modified version of the original MPL of Holt and Laury (2002). This approach makes the subjects reveal *certainty equivalents* (CE) for the lotteries. CE is the sure payment such that the subject is indifferent between receiving the prospect or the sure amount. The elicited CEs can be used to compare risk preferences across respondents as well as to measure the coefficients of relative risk aversion. Furthermore, following Alpizar *et al*., (2011), Engle *et al*., (2013), we conduct the same exercise with subject groups of 3 as well as subject groups of 6 to investigate the behavioral pattern when the subject is alone versus being with peer farmers.

The experiment is designed in a way that the participant's *certainty equivalents* for both the risky and ambiguous prospects are elicited. There are two uncertain prospects: a risky prospect and an ambiguous prospect. The risky prospect allows the participant to bet on the color of a ball drawn from a bag with 5 white and 5 yellow balls[1], a 50% chance to win the prize (see table A2). The ambiguous prospect, on the other hand, allows participants to bet on the color of a ball drawn from a bag containing 10 balls. The proportion of colors in the ambiguous bag is unknown, thus each ball can be either white or yellow and hence the probability of winning is unknown to the subject (see table A3). The participant can win Bangladeshi Taka (BDT) 400 by predicting the color correctly[2]. A choice list is used to elicit each participant's certainty equivalence for the above-mentioned two prospects.

Participants were provided 21 choices between a certain payoff and the risky prospect with the certain payoff increasing in 20 BDT increments from 0 BDT to 400 BDT. For small certain payments, it is expected that most participants would prefer to play the lottery. However, when the certain payoff is large, it is expected that participants will opt to take the payment instead of playing the lottery. Given this, participants' risk preferences are revealed as they switch at some point from playing a lottery to the sure thing. Following Eggert and Lokina (2007), and Akay et al., (2012), the CE for each participant in each game has been calculated as the midpoint between the lowest certain payoffs for which the participant chooses the sure thing and the highest certain payment for which (s)he chooses to play lottery.

The literature on measuring risk aversion mostly assumes a constant relative risk aversion (CRRA) utility function for the agents, $u(x) = x^{(1-\gamma)}$ where γ is the coefficient of the relative risk aversion. The ambiguity aversion (θ) can be estimated using the elicited certainty equivalent for both the risk and ambiguous situations (Akay *et al.*, 2012).

$$\theta = \frac{CE_R - CE_A}{CE_R + CE_A} \tag{1}$$

where CE_R = Certainty equivalent amount of money for the risky prospect, and CE_A = Certainty equivalent amount of money for the ambiguous prospect. This measure ranges from -1 (ambiguity loving) to 0 (ambiguity neutrality) to 1 (ambiguity averse). Similar to Engle *et al.*, (2013), our experimental design provides the scope for measuring the ambiguity aversion based on switchover points of both risky and ambiguous lotteries. The relative location of the switch-over point in the ambiguity instrument compared with the switch-over point in the risk instrument reveals the subject's ambiguity preferences.

In this study, we make sure that the participants do not communicate with other participants about their choices to be made. After the first round of each risk and ambiguity experiment is finished, we let participants form groups of 3 people and ask them to consider their group members as neighbors, friends etc. if they are not already. We then conduct the same experiments again, but this time participants are allowed to discuss with group members their decisions of whether to take the sure pay out or bet on the draw for each of 21 choices. We also tell them that even though they discuss the choices with their group members, each of the participants in the same group can make their own choices separately where the choices of each participant in the group may be same as or different from the choices of the other participants. In fact, we encourage each person to make their own decision after discussion. This approach is similar to the approach of Alpizar *et al.*, (2013) and Engle *et al.*, (2013). It helps us investigate if there is any effect of communication with neighbors or peer farmers on attitudes toward risk and ambiguity. Finally, we let them form groups of 6 members and conduct the same experiments we did in the second round. This new round allows us to investigate the effect of group size in assessing risky and ambiguous situations. Therefore, each farmer faces 126 choices in a total of three rounds. At the end, we randomly choose 20 farmers for payment. For each chosen farmer, we pick a round randomly for payment. If anyone of those farmers selected chose the sure payout in the selected round,

[1]This may be very simple game, but it is reasonable to get their behavior elicited provided that the farmer group has little to no formal education. With sophisticated lotteries, it might be difficult for farmers to understand the situation and hence to elicit their true attitude.

[2]The daily wage for an unskilled labor in this region is BDT 250-400 depending on the season.

we gave him/her that amount. Otherwise, he received the amount based on the result of the bet. In this way, we provided a monetary incentive to participants to elicit their attitudes toward uncertain situations.

5. Data Description

Table 1: *Descriptive statistics of the participants*

Variable	Mean	St. Dev	Min	Max
Age	39.7	11.84	18	75
Health Status (1-5 scale; 1=very good, 5=very poor)	2.3	1.01	1	5
Occupation (1= Agriculture, 0=Other)	0.83	0.38	0	1
Farmer's Own Education (Years of schooling)	4.78	4.83	0	15
1-5 Years (%)	0.28	0.45		
6-8 Years (%)	0.18	0.39		
9-10 Years (%)	0.19	0.4		
11-12 Years (%)	0.03	0.17		
$>$12 Years (%)	0.03	0.17		
Spouse's Education (Years of schooling)	4.69	4.69	0	12
1-5 Years (%)	0.22	0.42		
6-8 Years (%)	0.24	0.43		
9-10 Years (%)	0.2	0.4		
11-12 Years (%)	0.02	0.13		
$>$12 Years (%)	0			
Family Size	5.28	1.99	1	10
Male	2.82	1.22	1	6
Female	2.45	1.3	0	6
Marital status	0.89	0.31	0	1
Food affordable for consumption from household income (Months)	10.66	2.53	0	12
Electricity (1=If connected, 0 otherwise)	0.59	0.49	0	1
Membership of any Micro-finance institution (1=member, 0 otherwise	0.375	0.49	0	1
Land owned for farming (acres)	2.38	3.17	0	18.40
Membership in any village organization (1=member, 0 otherwise)	0.23	0.42	0	1
IPM user (1=uses any of IPM practices; 0 otherwise)	0.423	0.496	0	1
Extension AgentâĂŹs visit (1=Yes, at least once, 0 otherwise)	0.846	0.363	0	1
Sample size	104			

Table 1 provides the descriptive statistics of the participants in the experiments. The average participant is 40 years old with 5 years of own and spouse's education, and with 2.30 self-assessed health condition (medium health) in a scale of 1-5 (1 being very good, 5 being very bad). Twenty nine percent of participants do not have any formal education, with another 65% having 1-10 years. Eighty nine percent of subjects are married with an average household size of 5.28, and own 2.38 acres of land for farming. Participants were asked how many months in a year they usually have food sufficient to feed their family from their income. On average, participants lacked food for more than a month and less than two months per year. Fifty nine percent of participants have electricity in their houses. 38 percent are members of a micro-credit organization such as BRAC, Grameen, etc., and 23 percent are members of a village association such as a bazaar committee, school committee etc. An extension agent visited at least once in the last cropping season for 85 percent of the participants. Forty two percent of the subjects use at least one IPM practice in their pest-management.

6. Results

6.1. Eliciting Risk and Ambiguity Preferences

6.1.1 Risk Preferences

Table 2 (upper part) presents the summary statistics of the measured coefficients of constant relative risk aversion (CRRA) in all three circumstances. In all cases, the table shows that the farmers, on average, are risk averse. The risk preferences, however, change with the presence and absence of communication with other farmers and with the size of the group. When making choices alone, farmers are, on average, more risk averse (mean γ=0.59) than when they repeat the same exercise after discussions with two other peer farmers (mean γ=0.31). Farmers' risk aversion, however, is at its highest when he has five other peer farmers with whom to discuss their choices (mean γ =0.67). The average degree of risk aversion is similar to that reported in Tanaka *et al*., (2010) and Liu (2013) when farmers face uncertainty alone. The median risk aversion coefficient of 1.05 also shows that farmers are highly risk averse, and this degree of risk aversion is much higher than the median risk aversion of Ethiopian farmers (0.73) in Akay *et al*., (2012). Figure 1 plots the kernel density estimates of the relative risk aversion coefficient, γ. It shows that the distribution of the coefficient of risk aversion is roughly bimodal: one with a density corresponding to low risk aversion, γ, (or more risk loving) segment, and another density corresponding to the high risk aversion segment. While subjects in a group of 3 have lower risk aversion, as mentioned before, it is also evident from figure 1 that in the same situation farmers may also be less prone to make extreme choices as the modal points lie below those of two other cases. In this situation (group of 3), farmers are more prone to be risk neutral as the distribution line lies above the other two cases at γ=0. Farmers in groups of six tend to show more risk aversion than when deciding alone or in groups of three. However, they are also more risk loving, on average, than when deciding in groups of three. The figure indicates that farmers tend toward extreme decisions more when they face uncertainty either alone or when communicating with a larger group. Moreover, their attitudes tend less toward extreme choices when they communicate in a group of three.

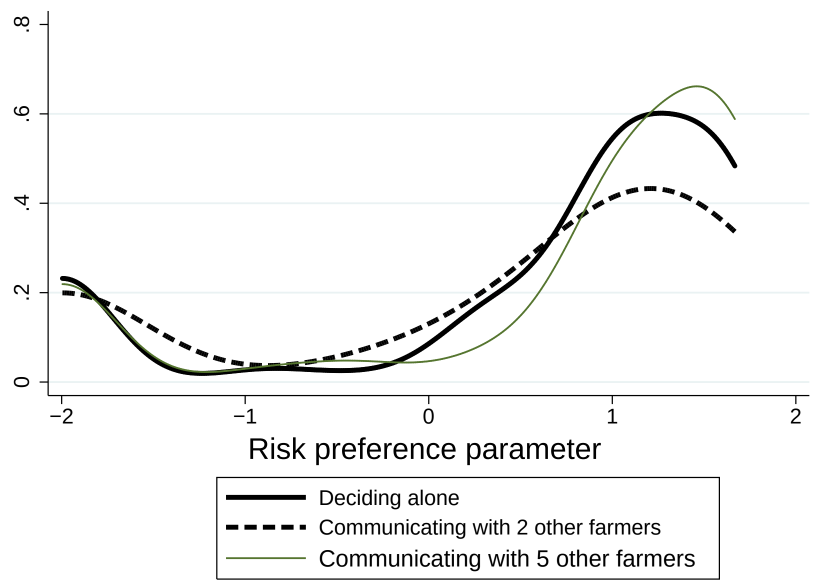
Figure 1 suggests that there are differences in attitudes (how they view or feel about risk) when faced with uncertainty in groups of different sizes (alone, 3, or 6). There may be some factors, such as how the characteristics of each farmer in a group are different, that increase/decrease the probability that some groups will fall into an extremely risk averse sub-group. Studying this phenomenon is, however, beyond of the scope of this paper and may be an avenue for future research. Table 3 presents the results of the distribution of estimated risk aversion coefficients and compares them with those in the literature. The table shows that Bangladeshi farmers are mostly risk averse in all situations: whether they face the uncertainty alone or in a group of different sizes. Compared to other findings in the literature, risk preferences of Bangladeshi farmers are similar, when facing the uncertainty in a group of 3, to those of Ethiopian farmers. Bangladeshi farmers are, however, more highly risk averse than Ethiopian farmers when decided alone and in groups of 6, though when considering risk aversion in general (mildly risk averse, risk averse, and highly risk averse), both pool

Table 2: *Summary statistics of the estimated risk and ambiguity aversion coefficients*

Coefficient*	Median	Mean	St. dev.	Min	Max
		Risk			
Risk Aversion (1)	1.05	0.592	1.26	-1.99	1.66
Risk Aversion (3)	1.05	0.319	1.39	-1.99	1.66
Risk Aversion (6)	1.05	0.67	1.29	-1.99	1.66
		Ambiguity			
Ambiguity Aversion (1)	0.013	0.187	0.457	-0.95	0.95
Ambiguity Aversion (3)	0	0.131	0.436	-0.95	0.95
Ambiguity Aversion (6)	0	0.168	0.406	-0.95	0.95

*Numbers in parentheses indicate the number people in the group, including the participant.

Figure 1: *Empirical distribution of risk aversion parameter*



of subjects exhibit similar pattern of risk preferences: they are mostly risk averse. Bangladeshi farmers, like Ethiopian farmers in Akay *et al*., (2012), are more highly risk averse than students in Dutch and U.S. universities. Since we have used the same experiment in three separate situations, we now pose the question of whether farmers' attitudes toward risk are the same, on average, when they face scenarios alone versus in groups of different sizes. We conduct a *t*-test of equality of means of the estimated parameters of CRRA in all scenarios that are presented in table 4 (upper panel). Table 4 indicates that farmers' CRRA coefficients, on average, are statistically different when they decide alone versus in groups of three and decide in groups of three versus in groups of six farmers. The means, however, are not statistically different when they decide

Table 3: *Distribution of constant relative risk aversion parameters of Bangladeshi farmers versus other estimates in the literature*

	Risk neutral/loving	Mildly risk averse	Risk averse	Highly risk averse
	$\gamma \leq 0.15$	$0.15 \leq \gamma \leq 0.41$	$0.41 \leq \gamma \leq 0.68$	$\gamma > 0.68$
	(%)	(%)	(%)	(%)
Dutch students (*n*=79)[a]	19	35	44	1
U.S. students (*n*=93)[b]	19	19	23	39
Bangladeshi farmers (*n*=104)[c]	19	11	1	69
Bangladeshi farmers (*n*=104)[d]	28	11	1	60
Bangladeshi farmers (*n*=104)[e]	21	4	1	74
Ethiopian farmers (*n*=92)[f]	22	11	10	58

a Trautmann *et al*., (2011); ***b*** Holt and Laury (2002, p. 1649, Table 3, last column). Identical tasks in Ethiopia and the Netherlands. A slightly different task has been used for U.S. student by Holt and Laury, with all choice options involving only non-degenerated gambles; ***c*** when each farmer decided alone; ***d*** when farmers decided in a group of 3 members; ***e*** when farmers decided in a group of 6 members; ***f*** Akay *et al*., (2012).

alone versus in groups of six farmers. It implies that, as shown in figure 1, mean risk aversion when deciding in groups of 3 is different from other two scenarios.

6.1.2 Ambiguity Preferences

There exists a vast stream of ambiguity aversion literature testing Ellsberg's (1961) thought experiment, mostly in laboratory settings in developed countries (such as Becker and Brownson, 1964; MacCrimmon and Larsson, 1979; Bowen and Zi-lei, 1994) . However, studies on field experiments measuring ambiguity preferences in developing countries is not so common (Engle-Warnick *et al*., 2007; Alpizar *et al*., 2011, Akay *et al*., 2012; Ross *et al*., 2012 are among recent studies). The reasoning behind Ellsberg paradox is that if a subject prefers, at any given prize, an uncertain amount over a certain amount when the probability is known, the subject is also expected to prefer the uncertain amount over a certain amount over the same given prize when probability is unknown. This implies that the agent prefers known uncertainty (risk) over unknown uncertainty (ambiguity).

Regarding the design of the experiment, since the sequence of the certain prospects are the same in both the cases where probabilities are known and unknown, we merely compare the certainty equivalent amount of money between two games to elicit each subject's ambiguity preference. Table 2 (lower panel) reports the summary statistics of the measured ambiguity preference parameter, θ. It shows that farmers, on average, are ambiguity neutral or averse, as their means lie in between 0.1 and 0.2, and medians are greater than or equal to 0. While testing the equality of means of different measures of ambiguity preferences, farmers on average do not show statistically different ambiguity attitudes in different circumstances (Table 4, lower panel). Table 5 provides the summary statistics of ambiguity preferences from certainty equivalence. It shows that farmers tend to be more ambiguity averse when facing the ambiguous situation alone than in groups. As they join in a group to face an ambiguous situation, they tend to be less ambiguity averse and more ambiguity neutral. Figure 2 provides visual support for Table 5.

Table 4: *t-test for the equality of the means of the estimated coefficients of risk (ambiguity) aversion*

Equality	t-stat. (p-val.)
CRRA Parameters	
Risk Aversion (1)=Risk Aversion (3)	**2.143 (0.034)**
Risk Aversion (1) = Risk Aversion (6)	-0.529 (0.598)
Risk Aversion (3) = Risk Aversion (6)	**-2.78 (0.007)**
Ambiguity Preference Parameters	
Ambiguity Aversion (1) = Ambiguity Aversion (3)	1.058 (0.293)
Ambiguity Aversion (1) = Ambiguity Aversion (6)	0.340 (0.735)
Ambiguity Aversion (3) = Ambiguity Aversion (6)	-0.633 (0.528)

Table 5: *Summary of ambiguity preferences from certainty equivalence*

	Deciding alone (%)	Group of 3 (%)	Group of 6 (%)
Ambiguity averse[a]	52	40	41
Ambiguity neutral[b]	27	46	41
Ambiguity loving[c]	21	14	18

a:$\theta > 0$; b:$\theta = 0$; c:$\theta < 0$

Figure 2 exhibits the empirical distribution of the estimated parameters for ambiguity aversion in all three scenarios. It shows that farmers' responses to ambiguous situations tend to be bimodal, dominated by the ambiguity neutrality if farmers face the situation alone. Their attitudes, on the other hand, tend to be multimodal dominated by the ambiguity neutrality when they made choices in groups of 3. When farmers face the ambiguous situations in groups (of 3, or 6) they tend to react in line with the similar uncertain situation when probability was known to them. This may provide a policy implication that ambiguous situations may not be completely inflexible if farmers have any source of information such as peer farmers who can provide them with better information to reduce the ambiguity. This information can be attained by providing more and better training to farmers so that farmers are more aware of the new technology and therefore become more likely to adopt. Table 6 presents the estimated ambiguity aversion coefficients for Bangladeshi farmers and those in the literature where similar procedures have been used. The table shows that Bangladeshi farmers generally are ambiguity neutral or ambiguity averse. Bangladeshi farmers are more ambiguity neutral and less ambiguity averse, in all three scenarios, than Dutch students and Ethiopian farmers. A common feature among all three studies is that elicitation method is the same: certainty equivalence with gains and existence of real incentives to earn money. As we did for the estimated risk aversion parameters, the second part of table 4 provides a t-test of the equality for the means of the estimated ambiguity preference parameters in different groups. It shows that statistically there are no differences in the means of the estimated ambiguity preference parameters in all groups: farmers face uncertainty alone, in group of three, and group of six farmers.

Figure 2: *Empirical distribution of ambiguity aversion parameter*

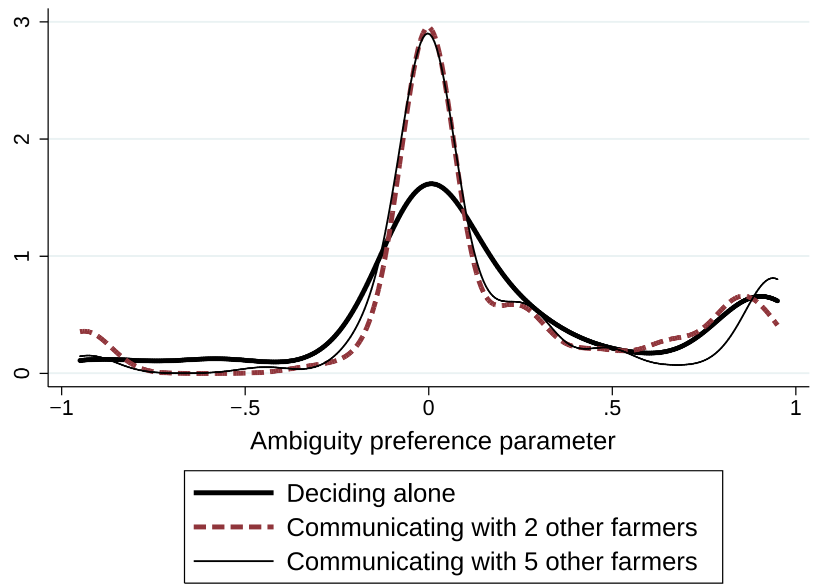


Table 6: *Distribution of ambiguity aversion parameters in Bangladeshi farmers versus other estimates in literature*

	Ambiguity seeking (%)	Ambiguity neutral (%)	Ambiguity averse (%)	Elicitation Method
	$\theta < -.4$	$-.4 \leq \theta \leq .3$	$\theta > .3$	
Dutch students (n=79)[a]	15	43	42	CE, gains, real incentives
British students (n=72)[b]	39	n.a.	61	Choice, gains, hypothetical
Business owners (n=130)[c]	56	n.a.	44	Choice, losses, hypothetical
Dutch students (n=39)[d]	3	46	51	WTP, gains, hypothetical
Bangladeshi farmers (n=104)*	8	63	29	CE, gains, real incentives
Bangladeshi farmers (n=104)**	7	70	23	CE, gains, real incentives
Bangladeshi farmers (n=104)***	4	74	22	CE, gains, real incentives
Ethiopian farmers (n=92)[e]	20	24	57	CE, gains, real incentives

* When each student/farmer decided alone; ** when students/farmers decided in a group of 3 members; *** when farmers decided in a group of 6 members; ***a*** Trautmann *et al*., (2011); ***b*** Roca *et al*., (2006); ***c*** Chesson and Viscusi (2003); ***d*** Kreen and Gerritsen (1999); ***e*** Akay *et al*., (2012)

Finding different CRRA parameters and ambiguity preference parameters for different experimental set ups raises an issue of whether the way uncertainty is faced, and hence risk and ambiguity preferences are measured, matters for how we classify respondents' behavior. We estimate the correlation between different

Table 7: *Correlation between risk and ambiguity measures*

	Risk (1)	Risk (3)	Risk (6)	Ambiguity(1)	Ambiguity (3)	Ambiguity (6)
Risk (1)	1					
Risk (3)	**0.525 (0.000)**	1				
Risk (6)	**0.302 (0.02)**	**0.544 (0.000)**	1			
Ambiguity (1)	**0.375 (0.000)**	0.010 (0.918)	-0.008 (0.936)	1		
Ambiguity (3)	0.052 (0.603)	**0.377 (0.000)**	-0.003 (0.978)	**0.258 (0.08)**	1	
Ambiguity (6)	0.034 (0.729)	0.055 (0.580)	**0.363 (0.000)**	0.097 (0.315)	-0.006 (0.951)	1

Note: Numbers in parentheses are *p*-values.

CRRA parameters and ambiguity parameters using Spearman correlation coefficients. Table 7 provides the results where the numbers in each cell is the correlation coefficient and the numbers in parentheses are *p*-values. It shows that the correlations across different scenarios are positive and high. More importantly, they are also statistically significant. The correlation between risk aversion and ambiguity aversion parameters is also positive, high, and statistically significant, corresponding to each of the categories: risk and ambiguity when facing alone, in a group of three, and in a group of six. The correlations between risk parameters and ambiguity parameters, in corresponding groups, are higher (lowest is 0.36) than those in Ross *et al.*, (2012) (highest is 0.21).

6.2. Demographic Characteristics and Attitudes toward Uncertainty

One of the primary goals of this paper is to determine the factors affecting attitudes toward risk and ambiguity, and the effects of those risk and ambiguity aversion coefficients on adoption of IPM practices by Bangladeshi farmers. For the first question, we estimate the following simple linear regression

$$U_i = \alpha + X_i\beta + e_i \tag{2}$$

where U_i is farmer i's attitudes toward uncertainty, both in risky and ambiguous situations, X is the set of the farmer's characteristics including age, household size etc., and e_i is an idiosyncratic error term. Eq. (2) will be used to determine factors affecting attitudes toward uncertainty for both risky and ambiguous situations.

We have used the socio-economic data collected as part of a field experiment to investigate if the subjects' socio-economic characteristics have any effects on their attitudes toward uncertainty. The socio-economic variables include personal information and family background such as age, education, marital status, whether the farmer's occupation is agriculture or not, household size, number of dependent persons in the household, total land owned for farming, and geographical location. Respondents during the baseline survey of the field experiment were asked about the food sufficiency for consumption given their income. In other words, they were asked how many months in a year, recalling last two years' experiences, they could feed their family with their income. The respondents in the experiment were asked to rate their health status from 1 to 5 where 1 implies the very good health and 5 implies very poor health condition.

Following Akay *et al.*, (2012), we avoid the dependence on the expected utility assumptions for risk attitudes by using the pure certainty equivalence multiplied by -1 as an index of risk aversion. Since a sizable fraction of participants (35 out of 104) revealed the two extremes, highest possible and lowest possible,

Table 8: *Regression analysis for factors affecting risk and ambiguity aversion for the Bangladeshi farmers when facing the uncertainty alone.*

	Risk aversion (Tobit)	Extreme risk aversion (Probit)	Ambiguity aversion (OLS)
Explanatory variables	Coeff.*	Marginal effect*	Coeff.*
Age	-1.017 (0.568)	0.005 (0.316)	.003 (0.497)
Education (years)	2.7 (0.553)	-.018 (0.130)	.013 (0.228)
Occupation (1=Agriculture, 0 otherwise)	19.04 (0.705)	-.222 (0.116)	**-.25 (0.052)**
Health status	-4.66 (0.800)	-.043 (0.387)	.043 (0.301)
Household size	-1.33 (0.955)	**.128 (0.034)**	**-.113 (0.041)**
Number of dependent in the household	-18.10(0.502)	-.087 (0.214)	**.114 (0.071)**
Food sufficiency (months)	**12.33 (0.098)**	.011 (0.566)	-.026 (0.161)
Total farm land owned	-0.014 (0.830)	5e-04 (0.766)	-1.13e-4(0.300)
Jessore (1=Jessore; 0=Magura)	**-74.13 (0.054)**	-.127 (0.211)	.065 (0.518)
Marital status (1=Married; 0 Otherwise)	36.44 (609)	-0.033 (0.867)	-0.059 (0.769)
Constant	-245.70 (**0.098**)		.61 (0.106)
Number of observations	104	104	104

* Numbers in parentheses are p-values. Robust standard errors for OLS have been used.

certainty equivalence, we control for censoring of our measures. Thus we use a Tobit model for our analysis of risk attitudes. We also include a Probit regression with a dummy variable that assumes the value of 1 if the certainty equivalence is censored at 1, and 0 otherwise to test whether socio-economic variables can explain the presence of extreme risk attitudes. Because there is no censoring for ambiguity attitude, we simply use OLS for explaining ambiguity attitude and estimate the equation (2). Explanatory variables are the same for all cases. The only difference is that the dependent variable is censored for tobit regression, dichotomous for the probit regression, and continuous for the OLS regression. Table 8 presents the regression results for measured attributes when farmers face uncertainty alone. The results of the similar analysis for risk and ambiguity aversion when farmers face uncertainty in groups of different sizes, 3 and 6, are presented in tables 9 and 10, respectively. A positive parameter implies increasing risk or ambiguity aversion, or increasing likelihood to reveal extreme level of risk aversion respectively. For the probit model, marginal effects are reported.

The regression results suggest that when facing uncertainty alone, having more months of sufficient food for family increases risk aversion which is not robust to all measures of risk aversion (Table 9 and 10). It may be difficult to explain this result as it differs from the general perception that wealthier individuals are more risk prone (Henrich and McElreath, 2002) and having more food sufficiency implies higher income. Since we do not have the total income/wealth data for the household, we cannot generalize the effect of food sufficiency (month) on risk aversion. We find that household size increases likelihood of extreme risk aversion, but decreases ambiguity aversion which is robust to different measures of risk aversion (Tables 9 and 10). While the number of dependents in the household increases the ambiguity aversion, being married reduces it. When farmers in groups of six are allowed to exchange information among themselves, having agriculture as the only occupation increases risk aversion, poor health increases ambiguity aversion.

Table 9: *Regression analysis of factors affecting risk and ambiguity aversion when facing uncertainty in a group of 3*

	Risk aversion (Tobit)*	Extreme risk aversion (Probit)*	Ambiguity aversion (OLS)*
Explanatory variables	Coeff.*	Marginal effect*	Coeff.*
Age	0.56 (0.787)	0.000 (0.961)	4.80E-04 (0.904)
Education	-2.877 (0.582)	-0.002 (0.879)	-0.001 (0.903)
Occupation (1=if agriculture; 0 Otherwise)	-6.508 (0.912)	-0.116 (0.401)	-0.141 (0.321)
Health status	34.022 (0.121)	0.067 (0.192)	0.024 (0.619)
Household size	15.762 (0.565)	**0.116 (0.066)**	**-0.109 (0.047)**
Number of dependent in the household	-26.438 (0.411)	-0.12 (0.105)	0.104 (0.108)
Food sufficiency (month)	**15.219 (0.08)**	0.015 (0.477)	-0.011 (0.477)
Farm land owned (decimals)	0.053 (0.486)	0.000 (0.884)	0.000 (0.552)
Marital status (1=Married; 0 Otherwise)	126.098 (0.127)	0.231 (0.203)	-0.111 (0.435)
Jessore (1=Jessore; 0=Magura)	-37.55 (0.396)	-0.048 (0.646)	0.137 (0.149)
Constant	**-509.59 (0.004)**		0.545 (0.16)

* Numbers in parentheses are p-values. Robust standard errors for OLS have been used.

6.3. Explaining Adoption Decisions

The second of the two broad issues of this paper is to investigate whether there is a separate role for behavioral preferences and, in particular, ambiguity preferences in explaining the adoption of innovations, IPM. We use a probit model to explain the role of attitudes toward uncertainty on IPM adoption . The traditional adoption equation is used to identify factors that affect different types of agricultural technologies. The following equation represents the adoption behavior

$$D_i = \delta + Z_i\psi + U_i\lambda + \epsilon_i \tag{3}$$

where D is an indicator variable (1 if adopts certain technology, say IPM, 0 if not), Z is the set of all other regressors including demographic variables, and U is the vector of attitudes toward uncertainty (risk and ambiguity parameters). The focus of eq. (3) is the coefficient of U, λ. If all or some of the vector λ is statistically significant, risk and/or ambiguity aversion affect agricultural technology practices.

Since we have used a subset of a bigger random survey data, we do not have full information about the adoption rate and other variables in the whole survey. Therefore, in this part we focus solely on the two variables: risk aversion and ambiguity aversion coefficients. Besides these two, the explanatory variables include several other correlates of adoption identified in the literature for which we have information collected through the household survey that we conducted for the field experiment: age, education, occupation, labor constraint, food sufficiency, total land owned, farm size, membership in any village association, MFI membership, marital status, extension agent's visits, geographical location, distance of the household from different important locations such as bazaar, highway, agricultural extension office and, another IPM farm. Similar to Ross *et al*., (2012), there are two concerns with our data. First, our data is cross-sectional and have been collected after the adoption, raising the concern that any ex-post measurement of explanatory variables could be affected by the adoption decision, therefore being endogenous (Besley and Case, 1993). Our explanatory variables, however, are unlikely to suffer from this problem as they are time-invariant in the short time period. Hence, those covariates are unlikely to be affected by the IPM adoption decision. A second concern is that,

Table 10: *Regression analysis of factors affecting risk and ambiguity aversion when facing uncertainty in a group of 6*

	Risk aversion (Tobit)	Extreme risk aversion (Probit)	Ambiguity aversion (OLS)
Explanatory variables	Coeff.*	Marginal effect*	Coeff.*
Age	0.84 (0.646)	**-0.01 (0.047)**	-0.004 (0.301)
Education	-3.698 (0.423)	-0.01 (0.413)	0.004 (0.651)
Occupation (1=if agriculture; 0 Otherwise)	**90.125 (0.083)**	-0.022 (0.868)	0.03 (0.757)
Health status	13.415 (0.475)	-0.005 (0.922)	**0.069 (0.081)**
Household size	-25.258 (0.274)	-0.005 (0.926)	**-0.112 (0.006)**
Number of dependent in the household	36.012 (0.184)	-0.002 (0.981)	**0.102 (0.029)**
Food sufficiency (month)	7.318 (0.338)	-0.007 (0.728)	0.002 (0.918)
Farm land owned (decimals)	0.046 (0.525)	**0.001 (0.011)**	8.40E-05 (0.714)
Marital status (1=Married; 0 Otherwise)	-17.235 (0.817)	0.15 (0.363)	0.113 (0.47)
Jessore (1=Jessore; 0=Magura)	-15.926 (0.683)	-0.024 (0.813)	0.007(0.931)
Constant	**-418.965 (0.007)**		0.195 (0.52)

* Numbers in parentheses are p-values. Robust standard errors for OLS have been used.

given the correlation between risk and ambiguity preferences, multicollinearity may be a statistical problem in equation (3). We circumvent this issue by estimating a separate probit model with each of the risk and ambiguity preference variables separately. Hence, three regressions will be used where both the risk and ambiguity aversion coefficients are present in one specification. The other two specifications include either risk aversion or ambiguity aversion coefficients only.

The estimates of the adoption equation that includes estimated behavioral variables when subjects faced the uncertainty alone are presented in table 11. The corresponding estimates when subjects faced uncertainty in groups of 3 and 6 are presented in Tables 12 and 13, respectively. We are mostly interested in the relative importance of risk and ambiguity aversion in the adoption of IPM practices. The estimates are not precisely estimated at the usual levels of significance of 5%. Our results suggest that, when farmers face the uncertainty alone, only risk aversion matters for technology adoption. A risk averse farmer is more likely to adopt IPM, which is robust to the specifications in table 9. One of the primary concerns of this paper is to investigate whether attitudes toward risky and ambiguous situations differ when subjects face the uncertainty alone versus when they are allowed to communicate with other peer farmers in groups of 3 and 6. As differences in attitudes occur in different situations, the question is raised that which of the farmers' behaviors should be considered in estimating the role of these behavioral variables on technology adoption. The results show that, focusing on the behavioral variables, though ambiguity aversion did not matter for technology adoption in case of facing uncertainty alone, it did while facing it in a group of 3. Similar to Ross *et al*., (2012), ambiguity aversion reduces the likelihood of IPM adoption when farmers are allowed to communicate with two other peer farmers about making decisions. Measuring the importance of ambiguity in our study extends beyond the results of previous attempts in literature (Engle-Warnick *et al*., 2007; Alpizar et al. 2011; Ross *et al*., 2012) as we demonstrate that the roles of risk and ambiguity preferences on the probability of technology adoption depend on what circumstances we provide farmers in the experiments: face alone or in a group of peers.

Table 11: *Regression analysis for the effects of risk and ambiguity aversion on IPM adoption by Bangladeshi farmers: uncertainty faced alone.*

Explanatory variables	Only Risk aversion	Only ambiguity aversion	Both are present
Age	-0.001 (0.837)	-0.002 (0.749)	-0.001 (0.846)
Education (years)	0.013 (0.361)	0.011 (0.450)	0.013 (0.355)
Occupation (1=Agriculture, 0 otherwise)	0.117 (0.427)	0.122 (0.417)	0.113 (0.448)
Health status	-0.002 (0.959)	-0.004 (0.948)	-0.002 (0.966)
Labor constraint	0.594 (0.149)	0.562 (0.163)	0.588 (0.154)
Food sufficiency (months)	-0.012 (0.642)	-0.019 (0.445)	-0.012 (0.640)
Total land owned	**0.001 (0.097)**	**0.001 (0.097)**	0.001 (0.109)
Farm size	**-0.001 (0.071)**	**-0.001 (0.071)**	**-0.001 (0.076)**
Distance from:			
Bazaar	**0.076 (0.080)**	**0.083 (0.060)**	**0.076 (0.080)**
Highway	0.04 (0.301)	0.032 (0.406)	0.040 (0.296)
Another IPM farm	-0.133 (0.599)	-0.106 (0.548)	-0.135 (0.607)
Agricultural Extension Office	0.021 (0.349)	0.017 (0.414)	0.021 (0.350)
Membership (1=If a member of any organization; 0 otherwise)	-0.024 (0.857)	-0.024 (0.857)	-0.022 (0.877)
MFI (1=If a member of any MFI such as BRAC, Grameen etc.; 0 otherwise)	0.106 (0.379)	0.084 (0.476)	0.108 (0.374)
Married	0.110 (0.623)	0.109 (0.618)	0.011 (0.621)
Extension AgentâĂŹs visit (1=if any agent visited; 0 otherwise)	-0.23 (0.149)	-0.254 (0.104)	-0.227 (0.148)
Risk aversion	**0.100 (0.035)**		**0.103 (0.043)**
Ambiguity aversion		0.081 (0.518)	-0.021 (0.877)
Jessore (1=Jessore; 0=Magura)	-0.056 (0.659)	-0.004 (0.971)	-0.056 (0.657)

Note: Numbers in parentheses are *p*-values.

7. CONCLUSION

Despite the importance and benefits of innovation, adoption of many new technologies in developing countries has been slow and incomplete. There has been a vast literature on identifying factors affecting technology adoption. Along with a number of market and non-market constraints, the effect of risk aversion is the behavioral determinant of this decision that has the dominant role in the discussion. Given that the level and distribution of outcomes from an innovation are unknown to the adopters in the early stages, it has an ambiguous nature (Ellsberg, 1961). However, little attention has been paid to measuring ambiguity aversion of poor people in developing countries or to finding the role of ambiguity aversion in technology adoption. Risk experiments in previous studies that measured the coefficients of risk aversion as well as ambiguity aversion have been designed such that individuals face the risky and/or ambiguous situations alone. Individuals in the real world, especially farmers in developing countries, are likely to obtain information from peer farmers before making any decision regarding a new innovation. Peer farmers or farmers' networks also matter for technology choices (Bandiera and Rasul, 2006). Hence, experiments that allow farmers to communicate among themselves provide a new avenue of research that is linked to the real world.

In this paper we address two broad issues. The first is to measure the size of the risk and ambiguity aversion coefficients of Bangladeshi rural farmers. It also investigates whether the attitudes toward uncer-

Table 12: *Regression analysis for the effects of risk and ambiguity aversion on IPM adoption by Bangladeshi farmers: uncertainty faced in a group of 3*

Explanatory variables	Only risk aversion	Only ambiguity aversion	Both are present
Age	-0.001 (0.784)	-0.002 (0.759)	-0.001 (0.798)
Education (years)	0.012 (0.401)	0.01 (0.494)	0.009 (0.537)
Occupation (1= Agriculture; 0 Otherwise)	0.106 (0.479)	0.074 (0.632)	0.051 (0.744)
Health Status	.0004 (0.995)	-0.004 (0.949)	0.012 (0.836)
Labor constraint	0.539(0.178)	0.516 (0.196)	0.557 (0.17)
Food sufficiency (months)	-0.019 (0.437)	-0.023 (0.363)	-0.017 (0.492)
Farm land owned (decimals)	0.001 (0.11)	4.80E-04(0.252)	4.70E-04 (0.27)
Farm size	-0.001 (**0.076**)	-0.001 (0.136)	-4.90E-04 (0.182)
Distance from:			
Bazaar	**0.082** (**0.062**)	**0.099** (**0.032**)	**0.099** (**0.038**)
Highway	0.033 (0.387)	0.029 (0.438)	0.031 (0.412)
Another IPM farm	-0.11 (0.575)	-0.199 (0.548)	-0.269 (0.428)
Agricultural Extension Office	0.017 (0.434)	0.021 (0.322)	0.024 (0.279)
Membership (1=If member in any organization; 0 Otherwise)	-0.016 (0.905)	-0.016 (0.903)	-0.014 (0.914)
MFI (1=If member in any MFI such as BRAC, Grameen, etc.; 0 Otherwise)	0.092 (0.448)	0.07 (0.56)	0.106 (0.391)
Married	0.117 (0.592)	0.108 (0.63)	0.135 (0.549)
Extension agent's visit (1=if any extension agent visited; 0 Otherwise)	**-0.256** (**0.099**)	**-0.335** (**0.039**)	**-0.334** (**0.04**)
Risk aversion	0.005 (0.892)		0.055 (0.213)
Ambiguity aversion		**-0.352** (**0.012**)	**-0.419** (**0.005**)
Jessore	-0.003 (0.981)	0.048 (0.712)	0.033 (0.796)

Note: Numbers in parentheses are *p*-values.

tainty (risk and ambiguity) differ when farmers face the uncertainty alone versus when they are allowed to communicate with peer farmers in groups of 3 and 6. In addition, the study attempts to find whether farmers' demographic characteristics affect their attitudes toward uncertainty. Another issue is whether farmers' aversion to ambiguity is important in explaining adoption decisions of IPM practices. Along with our experimental data, we have exploited a subset of a unique household survey dataset to explore these issues. The household survey collected information on Bangladeshi farmers' technology choices and socioeconomic characteristics.

We provide two conclusions. First, Bangladeshi farmers in our sample are risk and ambiguity averse. Levels and distributions of their risk and ambiguity aversion differ when they face an uncertain circumstance alone rather than when they communicate with other peer farmers before making decisions in uncertain situations. A farmer's demographic characteristics affect his/her attitudes toward uncertainty differently depending on which measure of attitudes toward uncertainty are used. Household size, however, affects a farmer's attitudes toward uncertainty in all cases. Second, and perhaps more importantly, our findings suggest that the roles of risk and ambiguity aversion on technology adoption depend on which measure of uncertainty behavior is incorporated in the adoption model. While risk aversion increases the likelihood of technology adoption when farmers face uncertainty alone, neither risk aversion nor ambiguity aversion matter when farmers face uncertainty in groups of six. When farmers face uncertainty in groups of 3, however, only ambiguity aversion matters for technology adoption it reduces the likelihood of technology adoption.

Table 13: *Regression analysis for the effects of risk and ambiguity aversion on IPM adoption by Bangladeshi farmers: uncertainty faced in a group of 6*

Explanatory variables	Only risk aversion	Only ambiguity aversion	Both are present
Age	-0.002 (0.78)	-0.001 (0.841)	-0.001 (0.817)
Education (years)	0.011 (0.437)	0.013 (0.381)	0.012 (0.422)
Occupation (1= Agriculture; 0 Otherwise)	0.13 (0.383)	0.111 (0.455)	0.128 (0.391)
Health Status	-.0005 (0.993)	-0.012 (0.838)	-0.008 (0.894)
Labor constraint	0.498 (0.216)	0.585 (0.151)	0.542 (0.188)
Food sufficiency (months)	-0.019 (0.439)	-0.023 (0.351)	-0.021 (0.393)
Farm land owned (decimals)	0.001(0.105)	1.00E-03 (0.105)	1.00E-03 (0.103)
Farm size	**-0.001** (**0.089**)	**-0.001** (**0.075**)	**-1.00E-03** (**0.087**)
Distance from:			
Bazaar	**0.086** (**0.057**)	**0.077** (**0.072**)	**0.082** (**0.069**)
Highway	0.038 (0.32)	0.041 (0.296)	0.042 (0.278)
Another IPM farm	-0.151 (0.626)	-0.173 (0.592)	-0.2 (0.567)
Agricultural Extension Office	0.018 (0.386)	0.016 (0.448)	0.018 (0.402)
Membership (1=If member in any organization; 0 Otherwise)	-0.019 (0.89)	-0.009 (0.948)	-0.012 (0.929)
MFI (1=If member in any MFI such as BRAC, Grameen, etc.; 0 Otherwise)	0.104 (0.381)	0.1 (0.398)	0.109 (0.363)
Married	0.102 (0.64)	0.105 (0.628)	0.098 (0.653)
Extension agent's visit (1=if any extension agent visited; 0 Otherwise)	-0.247 (0.112)	**-0.265** (**0.089**)	-0.255 (0.103)
Risk aversion	0.047 (0.286)		0.037 (0.429)
Ambiguity aversion		0.133 (0.356)	0.089 (0.566)
Jessore	-0.011 (0.927)	-0.017 (0.894)	-0.021 (0.868)

Note: Numbers in parentheses are *p*-values.

Since farmers in the real world face uncertain circumstances together, that leads them to communicate before making decisions. It is not unreasonable to believe that attitudes toward uncertainty revealed when they face uncertainty in a group are more appropriate than those when they face it alone. Our findings have potential policy implications. The vast majority of literature suggests that risk-aversion, without considering ambiguity aversion, is a possible root-cause for slow and incomplete technology adoption in developing countries. As a result, the literature suggests that money-back guarantees (Sunding and Zilberman, 2001) and crop insurance (Liu, 2013) are one of the means that potentially hedge against production risk as well as reduce the fear of loss associated with a new technology. Our findings suggest that Bangladeshi farmers are ambiguity averse. Moreover, when both calculated risk and ambiguity aversion parameters when farmers are allowed to communicate in a group of 3 are included in the adoption equation, ambiguity aversion reduces the likelihood of IPM adoption. It implies that a policy should be directed to ensure farmers' more and better access to information about the performance of the new innovation. This can be attained by better training, with dissemination methods that allows farmers to evaluate subjective probability of new innovations more accurately.

Unlike most experimental studies in developing countries, our field experiment findings are related to tangible decisions in the real world. There has been a long standing debate on the external validity of game experiments. Subjects in our study are decision makers, unlike experiments conducted in laboratory settings which hypothesize how risk and ambiguity might dictate decision-making. Similar to Ross *et al*., (2012), the results of our study suggest that game experiments, depending on the set-up of the experiment, can predict real decisions that strengthen their validity.

We designed the experiments in such a way that participants elicit their risk and ambiguity preferences across the domain of gains. When we designed our experiment, we assumed that expected utility theory (EUT) holds. Prospect theory (PT) (Kahneman and Tversky, 1979) describes a “reflection effect" in which a decision-maker exhibits risk-aversion in the domain of gains and is relatively risk-seeking in the domain of loss and can be used to predict the behavior of inexperienced individuals (List, 2003). Hence, potential future research might investigate the importance of risk and ambiguity preferences on a farmer’s technology adoption decision using experiments focused on prospect theory that considers preferences over both gains and losses.

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Appendix

Table A1. The ten binary choice tasks used in the experiments, patterned after Holt and Laury (2002)

Order in which tasks were shown				
Forward Order	Revised Forward Order	Reverse Order	**Lottery A** – "Safe" choice[a]	**Lottery B** – "Risky" choice[a]
	1		\$1.11 with **p=0**, \$0.67 with **p=1.0**	\$1.78 with **p=0**, \$0.22 with **p=1.0**
1	**2**	10	\$1.11 with **p=0.1**, \$0.67 with **p=0.9**	\$1.78 with **p=0.1**, \$0.22 with **p=0.9**
2	**3**	9	\$1.11 with **p=0.2**, \$0.67 with **p=0.8**	\$1.78 with **p=0.2**, \$0.22 with **p=0.8**
3	**4**	8	\$1.11 with **p=0.3**, \$0.67 with **p=0.7**	\$1.78 with **p=0.3**, \$0.22 with **p=0.7**
4	**5**	7	\$1.11 with **p=0.4**, \$0.67 with **p=0.6**	\$1.78 with **p=0.4**, \$0.22 with **p=0.6**
5	**6**	6	\$1.11 with **p=0.5**, \$0.67 with **p=0.5**	\$1.78 with **p=0.5**, \$0.22 with **p=0.5**
6	**7**	5	\$1.11 with **p=0.6**, \$0.67 with **p=0.4**	\$1.78 with **p=0.6**, \$0.22 with **p=0.4**
7	**8**	4	\$1.11 with **p=0.7**, \$0.67 with **p=0.3**	\$1.78 with **p=0.7**, \$0.22 with **p=0.3**
8	**9**	3	\$1.11 with **p=0.8**, \$0.67 with **p=0.2**	\$1.78 with **p=0.8**, \$0.22 with **p=0.2**
9	**10**	2	\$1.11 with **p=0.9**, \$0.67 with **p=0.1**	\$1.78 with **p=0.9**, \$0.22 with **p=0.1**
10	**(11)**[d]	1	\$1.11 with **p=1.0**, \$0.67 with **p=0**	\$1.78 with **p=1.0**, \$0.22 with **p=0**

Notes: [a]Winnings were not cash; participants won "1-prize" notes and selected from prizes worth approximately Rs. 10 (US\$0.22). [b]The interpretation choose Lottery A in all rows above and continues choosing Lottery B in all subsequent games. As discussed in the text, this interval is more difficult to who switch multiple times. [c]A participant who chooses Lottery B in this row has misunderstood the task, since it involves no uncertainty and the prize were not presented with this task in "revised forward" order. It is labeled as Task 11 because all task were standardized to his order for analysis.

Table A2: Certainty Equivalent Procedure risk experiments

Turn	Option one: Urn (P(Payoffs))	Option two: Certain Payments BDT	Switch-point from 1 to 2	CE at Switch-point BDT
1	0.5(0),0.5(400)	0	-	0
2	0.5(0),0.5(400)	20	1 to 2	10
3	0.5(0),0.5(400)	40	2 to 3	30
4	0.5(0),0.5(400)	60	3 to 4	50
5	0.5(0),0.5(400)	80	4 to 5	70
6	0.5(0),0.5(400)	100	5 to 6	90
7	0.5(0),0.5(400)	120	6 to 7	110
8	0.5(0),0.5(400)	140	7 to 8	130
9	0.5(0),0.5(400)	160	8 to 9	150
10	0.5(0),0.5(400)	180	9 to 10	170
11	0.5(0),0.5(400)	200	10 to 11	190
12	0.5(0),0.5(400)	220	11 to 12	210
13	0.5(0),0.5(400)	240	12 to 13	230
14	0.5(0),0.5(400)	260	13 to 14	250
15	0.5(0),0.5(400)	280	14 to 15	270
19	0.5(0),0.5(400)	300	15 to 16	290
17	0.5(0),0.5(400)	320	16 to 17	310
18	0.5(0),0.5(400)	340	17 to 18	330
19	0.5(0),0.5(400)	360	18 to 19	350
20	0.5(0),0.5(400)	380	19 to 20	370
21	0.5(0),0.5(400)	400	20 to 21	390

* 0.5 is the probability of winning the lottery.

Table A3: Certainty Equivalent Procedure for ambiguous experiments

Turn	Option one: Urn (P(Payoffs))	Option two: Certain Payments BDT	Switch-point from 1 to 2	CE at Switch-point BDT
1	?(0),?(400)	0	-	0
2	?(0),?(400)	20	1 to 2	10
3	?(0),?(400)	40	2 to 3	30
4	?(0),?(400)	60	3 to 4	50
5	?(0),?(400)	80	4 to 5	70
6	?(0),?(400)	100	5 to 6	90
7	?(0),?(400)	120	6 to 7	110
8	?(0),?(400)	140	7 to 8	130
9	?(0),?(400)	160	8 to 9	150
10	?(0),?(400)	180	9 to 10	170
11	?(0),?(400)	200	10 to 11	190
12	?(0),?(400)	220	11 to 12	210
13	?(0),?(400)	240	12 to 13	230
14	?(0),?(400)	260	13 to 14	250
15	?(0),?(400)	280	14 to 15	270
19	?(0),?(400)	300	15 to 16	290
17	?(0),?(400)	320	16 to 17	310
18	?(0),?(400)	340	17 to 18	330
19	?(0),?(400)	360	18 to 19	350
20	?(0),?(400)	380	19 to 20	370
21	?(0),?(400)	400	20 to 21	390

Note:? Implies that probabilities are unknown.