Ambiguity Aversion and Portfolio Choice in Small-Scale Peruvian Farming

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December 2008

Abstract:

While the effect of risk aversion on farmers' decision-making has long been documented, far less is known about the effect of ambiguity aversion. We argue that ambiguity aversion is just as relevant to their decision-making process because they are uncertain about the yield distributions generated by available technologies. By experimentally measuring risk and ambiguity aversion in rural Peru, we provide new evidence on the role of ambiguity aversion on farm decisions in developing countries: ambiguity aversion, not risk aversion, reduces the likelihood that farmers plant more than one variety of their main crop.

Keywords: Ambiguity aversion; Risk and ambiguity measurement instruments; Experimental economics; Technology Choice.

JEL classification nos. O12, O33, C91.

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Acknowledgements: We thank Leah Brooks, Cathleen Johnson, Dean Karlan, Claude Montmarquette, Ragan Petrie, Debraj Ray and seminar participants at McGill University, New York University, the Bank of Canada, Carleton University, Canterbury University, CIRANO and conference participants at NEUDC2006, CEA2007 and LACEA2008. We thank Duncan Whitehead, Rafael Novella and Patrick Hartford for excellent research assistance, as well as our field surveyors Luis Suarez, Francisco Barrios and Fernando Manrique. We gratefully acknowledge funding from the Social Science and Humanities Research Council of Canada, the Association of Universities and Colleges of Canada as well as the Faculty of Arts, McGill University. We thank the Centre for Interuniversity Research and Analysis on Organizations (CIRANO) and the Bell University Laboratory in Electronic Commerce and Experimental Economy for use of the experimental laboratory.

1 Introduction

Decision-making under uncertainty touches upon many dimensions of economic behavior. For example, investors must decide which assets to hold, producers must decide which technologies to use and households must decide in which neighbourhoods to live. All of these decisions are made in an environment where the payoffs are uncertain. In most cases, the realization of the payoffs is unknown, making decisions risky. And often, the likelihoods with which the payoffs occur may also be uncertain, making decisions ambiguous: the investor may not know the probability of a high return to an asset, the producer may not know the probability distribution of the yield generated by a new technology, and the household may not know the probability distribution of future neighborhood property values.

The economics profession has extensively studied the role of risk aversion in agents' decision-making under uncertainty. Recent theoretical advances have also explored the role played by ambiguity aversion (Gilboa and Schmeidler (1989) and Klibanoff et al. (2005)). While risk aversion's impact on decisions has been thoroughly investigated empirically, the same is not true of ambiguity aversion's impact. On the one hand, household, labor force or consumer surveys do not typically include information necessary to evaluate an individual's ambiguity aversion. On the other hand, experimental methods to measure ambiguity aversion are only just surfacing (Anagol et al. (2008) and Engle-Warnick and Laszlo (2008)).

We contribute to the literature on decision-making under uncertainty by experimentally measuring individuals' attitudes towards risk and ambiguity and investigating their effects on one particular decision: crop choice among farmers in a developing country. Ambiguity theory allows for the relaxation of the assumption that farmers know with what probability events associated with technology choices occur. The implication is that, for some crops and varieties, modeling the problem as choice under risk assumes that the farmers know more than they actually do about distributions over yields or revenues. In our paper, we test the hypothesis that for these technologies ambiguity is the more appropriate model to apply.

The importance of ambiguity aversion in portfolio choice decisions is not new (e.g. Klibanoff et al. (2005)). However, there is little evidence of its importance in portfolio choice decisions of small-scale farmers from developing countries. If risk aversion matters, there is little that policy makers can do other than to help improve *ex-post* risk coping mechanisms by helping farmers access formal credit and insurance markets, which is difficult to do in poor countries. However, if ambiguity aversion matters, then policy makers can help via *ex-ante* mechanisms in which farmers resolve the uncertainty through education, agricultural research, technical assistance or agricultural extension services. Because the policy prescriptions for the two cases is so different, knowing the relative importance of the two behavioral effects is key for guiding policy geared towards alleviating the negative effects of risk on the rural poor.

In 2006, we conducted artefactual field experiments (Harrison and List, 2004) in rural Peru, where agricultural risk is high and *ex-post* risk coping mechanisms (formal credit and insurance markets) are thin and where 65% of the population lives below the poverty line (INEI, 2008). We also collected socio-economic survey data which, combined with our experimental results, allow us to uniquely explore the roles of risk and ambiguity aversion on farmers' decision-making.

We find that ambiguity aversion, and not risk aversion, is a significant predictor of whether a farmer diversifies across varieties. Specifically, a farmer's attitude towards ambiguity reduces the likelihood that she plants more than one variety of her main crop, while her attitude towards risk seems to have little to no measurable effect on this decision.

The next section describes the experimental design which allows us to measure farmers' risk and ambiguity aversion. The third section describes a portfolio choice model that takes into consideration both risk and ambiguity aversion. The model generates testable implications, which we take to our data described in section four. The fifth section provides the results of our analysis and conducts robustness checks. The sixth section concludes.

2 Experimental Design

This section first describes how we measure farmers' risk and ambiguity aversion, as well as a measure that we use to diagnose whether our subjects understand the experiment. The risk and ambiguity instruments are identical to those in the laboratory validation experiments reported in Engle-Warnick and Laszlo (2008). We then outline our experimental procedures where we describe our subject pool and sessions.

2.1 Risk Aversion Measure

Figure 1 shows the instrument, inspired by Eckel and Grossman (Forthcoming) and denoted 'five options' (FO), which we use to derive our preference measure. Our subjects are instructed to select exactly one of the five options. Each option is represented by a circle which contains two payoffs, each with a 50% probability of occurring. To illustrate, the top option pays 26 Nuevos Soles (S/.) with certainty, while the option to its right has a low payoff of 2 S/. with 50% probability and a high payoff of 62 S/. with 50% probability.[1] The variance in the payoffs increases as we move counter-clockwise from the top option.

Our instrument for measuring risk aversion is derived by decomposing FO into a set of four binary choices. This decomposition resembles the instrument in Holt and Laury (2000), and allows us to design an ambiguity instrument that mirrors this instrument. Figure 2 presents this decomposition. Each row in the figure corresponds to a single binary choice between two alternative gambles. Specifically, each row depicts a choice between two alternatives that are contiguous in the FO instrument. Beginning with the first row of choices and moving down, an expected utility maximizer will at some point switch from the left-hand side gamble with lower variance to the right-hand side gamble with a higher variance and slightly higher expected utility. The sooner the subject switches from the left-hand side to the right-hand side, the less relatively risk averse she is.

[1] 10 S/. were approximately equal to $3 US in 2006.

2.2 Ambiguity Aversion Measure

Our instrument for measuring ambiguity aversion is depicted in Figure 3, which presents five decisions, one in each row. In the figure, the gamble on the left displays the possible prizes, but not the probability of winning those prizes (this is communicated by eliminating the vertical line in the center of the circle). The gamble on the right contains the same prizes, but with a 50/50 chance of winning each one. However, if a subject chooses the gamble on the right, she must pay 0.50 S/. of her final earnings back to the experimenter for making this choice. Thus the left gamble is ambiguous in the sense that the subject does not know the probability distribution over outcomes, and the costly right gamble provides the subject with an opportunity to reveal her preference to avoid this ambiguity.[2]

2.3 Diagnostic Measure

Engle-Warnick et al. (2009) document an important preference for payoff-dominated alternatives among a different sample of peruvian farmers. Specifically, they find that those subjects chose payoff-dominated alternatives 25% of the time they were available among a set of three alternatives.[3] Since the choice of a dominated alternative calls into question subjects' understanding of the experiment, or subjects' motivation for participating in the experiment, we obtain a measure of this preference and use it as a diagnostic tool to check the robustness of our results.[4]

Figure 4 shows the five choices subjects faced with a payoff-dominated gamble. For each of the five base gambles, we simply test whether subjects would prefer a gamble that is

[2] This standard method of eliciting aversion to ambiguity has its roots with the Ellsberg Paradox (1961), in which an ambiguity neutral subject would never pay to avoid the ambiguous gamble.

[3] Hamoudi (2006) also reports 'gamble averse' subjects, who prefer a sure amount of money over a gamble, where the lower of the two amounts that can be won in the gamble is equal to the sure amount.

[4] We thank a seminar participant for suggesting that failure to get the first-order problem right (i.e., payoff dominance), can call into question the usefulness of testing for the second order problem (i.e., risk preference). Engle-Warnick et al. (2009) believe that there are reasons that subjects may legitimately prefer a payoff-dominated choice.

dominated in both possible payoffs. This instrument can be thought of as a measure of the subjects' ability to understand the decision-making problem, or a measure of a type of subject who for some reason legitimately prefers to leave money on the table.

2.4 Experimental Procedures

2.4.1 Subject Pool

In February of 2006, we held two sessions in the district of Cañete (on the Coast) and five sessions in the Mantaro river valley (in the Central Sierra). All seven communities are rural communities, where agriculture is the main livelihood. Though these communities do not specialize in a particular crop, maize and potato are the dominant crops. These crops are typical Peruvian crops and are both consumed locally and sold in larger domestic markets.

In Cañete, we held one session with 19 subjects in Unanue (a community with 283 dwellings), and the other with 25 subjects in La Pampilla (134 dwellings). In the Mantaro river valley, we alternated sessions on either side and each community was located in a different district.[5] In the district of Paccha, we ran a session with 25 subjects from the community of Buenos Aires (52 dwellings). In the district of Acolla, we ran another session with 25 subjects in Tambopaccha, a community with 90 dwellings. In the district of Matahuasi, we had 25 subjects from Yanamuclo (213 dwellings). In the district of Orcotuna, we had 15 subjects from the community San Antonio (52 dwellings). Finally, in the district of Sicaya, we had 25 subjects in Anexo La Libertad (101 dwellings). The population data are from the 2005 Peruvian census, available on-line at `www.inei.gob.pe`.

We visited each of the seven communities several days in advance to recruit subjects and arrange locales for the experiments with the help of community leaders, whose involvement

[5] We did this to minimize potential contamination from one session to the other in this densely populated region. Because kinship ties are strong in contiguous communities and weak across the river and non-contiguous communities, it is unlikely that word would travel quicker than the experimenters and surveyors from one field site to the other.

was necessary to ensure the community's cooperation. We recruited subjects based on the following criteria: they had to be farmers of legal age (18 or above), reside in the community where the session was to be held, and had to have basic literacy and numeracy skills.

Since the community leaders played an important role in recruiting subjects for the session, it is unlikely that we have a random sample. However, given the small sizes of the communities that we visited, our subjects are representative of their communities. For instance, since subjects did not come from the same households, a session with 25 subjects would represent 25 different households. Thus, in a community with 52 dwellings (such as Buenos Aires), our session involved subjects from almost 50% of households. At the very least, in the case of Yanamuclo, we sampled from just over 10% of households.

2.4.2 Experimental Sessions

We ran our sessions as laboratory experiments in the field. Subjects were given a show-up fee of 10 S/. upon arrival to cover their transportation and opportunity cost, which is roughly what an agricultural laborer earns in a day. We paid the show-up fee immediately to build trust in the incentivized part of the experiment. Two of our surveyors, each native Spanish speakers, read the instructions from a script.[6] The subjects were given a booklet containing forty-four pages, each page containing one decision.[7] For each decision, subjects indicated their choice by pen. After subjects completed their booklets we verified that each page had exactly one choice marked on it. To control for the effects of order in presenting the choices, the order of the decisions as well as the left/right presentation of the gambles was randomly determined for each subject.

The gambles were implemented by drawing chips out of a bag. For this we used three separate bags, one for each type of randomization required by the experiment. The first bag

[6] An English version of the instructions are provided in Appendix 1 (the Spanish version is available upon request).

[7] These decisions consisted of the fourteen risk, ambiguity and payoff-dominated choice decisions plus the questions with additional alternatives in the choice set, which we do not analyze here.

contained forty-four numbered chips and determined which page of the booklet would be selected for payment. The second bag contained five blue and five yellow chips and determined the outcome of a 50/50 gamble with known probabilities. The third bag contained a number of blue and yellow chips which we determined randomly by drawing from a uniform distribution from all possible combinations of yellow and blue chips just before the session. When subjects played the gambles, they were first asked which color they chose, blue or yellow, to represent the higher of the two possible payoffs.[8] They then pulled a chip from the appropriate bag to determine their earnings. Subjects were permitted to see the composition of the chips in the ambiguous bag if they desired after the draw. No subject ever asked to do so. Subjects also pulled the chip that determined the choice that was played for pay.

The experiments were held in either a schoolroom or a public meeting room. Only the subjects and experimenters were in the room at the time of the experiments, and outside distractions were carefully minimized. Subjects with relatively poor vision or hearing were seated at the front of the room to facilitate understanding of the instructions.

One-hundred and sixty subjects participated in the experiments, with session sizes of approximately twenty.[9] Subjects earned an average of 25 S/. in addition to the 10 S/. show up fee. The experiments lasted approximately one hour, and the entire time spent on the experiments and the survey was approximately 4 hours per session. Subjects first participated in the experiment, then individually completed the survey, and then were paid their earnings from one randomly chosen gamble choice in private.

[8] Charness and Gneezy (forthcoming) used this experimental procedure.

[9] Sample sizes in lab experiments in the field studying risk preferences in developing countries tend to be quite small. Our study compares in sample size with Binswanger (1980) who had 240 farmers and Shahbuddin et al. (1986) who had 202 farmers.

3 A Model of Portfolio Choice

The portfolio choice model follows Dercon (1996) and Klibanoff et al (2005). We are interested in understanding how portfolio choice is affected by risk and ambiguity aversion. Though the model describes crop diversification, it is generalizable to other contexts: indeed, we consider different crop varieties as well as different crops in the empirical analysis.

Consider a farmer who must choose how much of the risky crop and how much of the safe crop to plant. The existence of a riskless crop is frequently made in this literature (see also Feder (1985)). Just and Zilberman (1983) argue that this is a reasonable assumption if one considers the safe crop to be a traditional one and the risky one to be a modern one, if farmers indeed view the new crop as riskier.

Consider that there are two states of the world $i = \{1, 2\}$, where state 1 is the good state (e.g. high yield) and state 2 is the bad state (e.g. low yield). State 1 occurs with probability p and so state 2 occurs with probability $(1 - p)$. Let x_s be the output (payoff) from planting the safe crop, which is invariant to the state of the world. Let x_{ri} be the output (payoff) from planting the risky crop in state i such that $x_{r2} < x_s < x_{r1}$.

The farmer must choose what proportion α of her wealth (or land), normalized to 1, to invest in the safe crop to maximize her expected utility, where ρ is the coefficient of relative risk aversion, and τ is the coefficient of ambiguity aversion. To understand the farmer's decision problem, consider her expected utility over her diversified portfolio in the known-probability case:

$$U(x; \alpha, p, \rho) = Eu(\alpha x_r + (1 - \alpha)x_s; \rho) \tag{1}$$

where $U(\cdot)$ is a standard utility function. The interpretation of this expected utility function is the standard one in the literature in decision-making under uncertainty. Specifically, concavity of the expected utility represents risk aversion, linearity is risk neutrality and convexity is risk preferring.

Following Klibanoff et al. (2005), one approach to modeling this decision problem in an unknown-probability (ambiguity) environment is to apply the following function to $U(\cdot)$:

$$EV(x;\alpha,p,\rho,\tau)=\int_p v(U(x;\alpha,p,\rho),\tau)dp \tag{2}$$

For intuition behind the expected utility expression in (2), consider the farmer who does not know the probability with which the good state will occur. Then she takes the expected value of her utility over all possible probabilities. The interpretation of $v(\cdot)$ is the same as with the expected utility function $U(\cdot)$: concavity represents ambiguity aversion, convexity represents ambiguity preferring, and linearity represents ambiguity neutrality.

Why distinguish between risky and ambiguous crops for farmers? Imagine a farmer who must decide which crops to plant in the next season. While she may know fairly well the probabilities with which a particular crop will have a high or a low yield, she generally does not know *ex ante* whether the high or the low yield will realize. This is the risky case, because the uncertainty concerns only which state of the world will realize in the future. However, she may also not know the probability with which the crop will have a high yield. Thus, the uncertainty is about the yield probabilities, in addition to the uncertainty about which state of the world will realize. This is the ambiguity case. Suppose that she learns about the yield distribution of the new crop, either through her experience, the experience of others, or agricultural extension services, then the ambiguity can be resolved. Without ambiguity, then x_r is a risky crop because it pays x_{r1} in the good state of the world with known probability p, but $x_{r2} < x_{r1}$ in the bad state of the world with known probability $(1-p)$. With ambiguity, then x_r is an ambiguous crop, because p is not known with certainty.

It is important to consider the ambiguous, rather than risky case, because when farmers are choosing their portfolios, they often do so with little knowledge of possible crops' the yield distributions. Because new crops and varieties frequently enter the market, these crops could be seen more as ambiguous than risky.

We illustrate portfolio choice using gambles from our instruments in order to qualify how portfolio choice decisions are affected by risk and ambiguity aversion. While a closed form solution exists in which risk aversion causes diversification into the safe asset when only a risky and safe asset exist, the ambiguity case has no closed form solution. We thus provide numerical solutions consistent with the approach taken in Klibanoff et al. (2005). For computational convenience we use the same Constant Absolute Risk Aversion (CARA) functional form to represent both risk ($-\frac{1}{\rho}\exp -\rho x$) and ambiguity preferences ($-\frac{1}{\tau}\exp -\tau x$). Qualitative results from these computations do not depend on the functional form of the utility function.

Let the safe asset pay 26 in each state of the world; the risky asset pay 20 or 35 with equal probability; and the ambiguous asset pay 14 or 44 with equal probability. Let the probability distributions over outcomes be represented exactly as in our instruments, with ten chips in a bag, all either blue or yellow. Some degree of risk aversion would allow the choice of the risky asset (because the expected value is greater than 26), and the same holds true of the ambiguous asset.

Assuming a uniform prior over the distributions of outcomes, and noting that there could have been from zero to ten chips representing the higher of the two outcomes, the subject chooses the ambiguous lottery if

$$\frac{1}{11}\sum_{i=0}^{10} V((\frac{i}{10}u(14) + \frac{10-i}{10}u(44)),$$

the subjective utility of the risky asset is

$$V(\frac{1}{2}u(20) + \frac{1}{2}u(35)),$$

and the subjective utility of the safe asset is

$$V(u(26)).$$

While expected utility preferences are typically represented as a utility function over outcomes, ambiguity preferences are represented by a subjective utility function over simple gambles. As is usually explained in the Ellsberg Paradox, an ambiguity neutral subject would never pay to avoid ambiguity: any payment for avoidance results in a strictly lower utility level when $V(\cdot)$ is linear.

3.1 Safe and Risky Portfolio Allocation

For different degrees of risk aversion we numerically compute the optimal allocation of wealth between the safe and the risky asset. The idea is to show how investment in the risky asset changes with risk aversion, holding ambiguity preference constant. Wealth is normalized to 1, thus the results can be interpreted as proportion of wealth invested in each asset.

The results are displayed in Table 1, in the section labeled “Risky Only.” Moving down the the first three rows of the table, risk aversion decreases from a CARA parameter of 1.0, to 0.5, to 0.1, holding ambiguity aversion constant. As risk aversion decreases, the proportion of wealth invested in the risky asset increases from 2.5% to 27%. In other words, investment in the risky asset is decreasing in risk aversion.

3.2 Safe and Ambiguous Portfolio Allocation

We repeat the procedure in a world with only safe and ambiguous assets, and present the results in the column labeled “Ambiguous Only” in Table 1. In the bottom three rows of the table, ambiguity aversion increases from a CARA parameter of 1.0, to 2.0, to 3.0 while risk aversion is held constant. As ambiguity aversion increases, the proportion of wealth invested in the ambiguous parameter decreases from 9.1% to 5.5%.

In this case it is important to also check the effect of risk aversion on portfolio choice. The top three rows of the table show that risk aversion works in the same direction, holding ambiguity aversion constant at a CARA parameter of 0.1, as risk aversion increases, the proportion of wealth invested in the ambiguous asset decreases from 12.9% to 1.3%.

3.3 Safe, Risky, and Ambiguous Portfolio Allocation

We repeated the procedure with all three assets available to the farmer, and present the results in the column labeled "Risky and Ambiguous" in Table 1. As before, reading down the first three rows of the table illustrates the change in portfolio allocation as risk aversion decreases, holding ambiguity aversion constant. The results show that relative to each other, risk and ambiguity preferences can work in different directions.

The table shows that investment in both the risky and ambiguous asset is decreasing in risk aversion, and the ratio of risky/ambiguous asset holdings is also decreasing. This is because the agent finds it optimal to diversify away from the safe asset and, as long as the risky and ambiguous assets are imperfectly correlated, a more diversified portfolio is preferred to a less diversified one.

The bottom three rows show optimal portfolio choice holding risk preference constant and increasing aversion to ambiguity. Here, investment in the ambiguous asset is decreasing in ambiguity aversion. Investment in the risky relative to ambiguous asset is also increasing in ambiguity aversion. This is because the ambiguous asset becomes "a less effective diversifier and less valuable."

3.4 Testable Implications

As long as the farmer is not infinitely risk averse or the expected yield of the risky crop is different than that of the safe crop, then the farmer will find it optimal to plant some of both crops. However, the more risk averse the farmer is, the less she diversifies away from the safe crop. If she has little information about the probability that the high outcome occurs, her portfolio diversification also decreases in ambiguity aversion. If she chooses among only risky crops, then we should only find that risk aversion is a significant predictor of her portfolio choice. However, if she chooses among ambiguous crops, then, holding fixed her risk aversion, ambiguity aversion should also reduce her diversification away from the safe crops.

Furthermore, the effects of uncertainty should be stronger where *ex-post* risk management strategies are unavailable. Thus, we would expect the effects of risk and ambiguity aversion to be stronger among farmers who have less access to formal credit or insurance.

In deriving the model, we follow the literature in its assumption that the farmer has the option of choosing a riskless crop (e.g. Feder (1980) and Dercon (1996)). As in Just and Feder (1983), who generalize the crop choice problem to stochastic crops, this assumption is 'reasonable' if farmers subjectively view one crop as being lower risk than the other. This literature also posits that traditional crops are viewed by farmers are typically being viewed as lower risk (and lower yield) as new or modern crops.[10]

The empirical analysis considers both crop and varietal diversification. The model predicts that both risk and ambiguity aversion will cause less diversification away from the safe crop or variety. We expect ambiguity aversion to be particularly strong in the case of varietal diversification. Thanks to innovations in agricultural technology, farmers are often presented with new varieties with which they have little or no experience. They are often reluctant to adopt these varieties because not only do they not know whether they will get a high or a low yield at harvest (which is also true for the varieties they know well and already plant), but they might not even know the probability with which the high or low yield will occur.

4 Data & Construction of Variables of Interest

4.1 Survey

After the experiment, subjects were directed towards the surveyors with whom they orally completed a survey lasting 30 to 45 minutes per subject. The survey contained several

[10] New and modern crop varieties may actually show lower yield variability in field trials because they are designed to be more drought, cold or pest resistant. However, the decision to plant a particular variety is driven by *ex-ante* uncertainty about yield variability on the farmer's plot rather than *ex-post* measured variability on an experimental plot.

modules designed to shed light on farm decisions, as well as relevant socio-economic controls, including demographics, education, dwelling construction and materials, economic activity, access to infrastructure and services and agricultural production. The empirical analysis considers only 136 subjects because of missing observations for some variables and because 13 of our subjects planted no crops at all in the last year. The descriptive statistics of our sample and the variables that will be used in the empirical analysis are found in Table 2.

4.2 Diversification

This subsection describes the construction of our dependent variables: crop and varietal diversification. Dercon (1996) uses the proportion of inputs allocated to the safe crop (sweet potato in his case). Others use a Herfindahl/Hirschman type of index (Pope and Prescott, 1980) which is a measure of the extent of diversification. Because of data limitations, we consider only measurements of the incidence (rather than extent) of diversification: whether the farmer diversifies her crops and whether she diversifies varieties of the main crop.

We asked respondents questions about their agricultural experiences over the last year. Specifically, we asked questions pertaining to the top three crops planted in the last 12 months such as the years of experience with each crop and whether they at any time received technical assistance. For the main crop, we then asked questions about the top three varieties they planted in the last 12 months, the name of each variety, the years of experience with the particular variety and whether they've received any technical assistance.[11]

We create two binary measures of diversification: whether the farmer produces more than one crop (diversifies across crops) and whether the farmer plants more than one variety of the main crop (diversifies across varieties). In our sample, 67.6% of farmers plant more than

[11] We also have information on the land dedicated to each of the top three crops and top three varieties, so a Herfindahl/Hirschman index would be feasible in principle. However, responses to these questions are unreliable as these often summed to more than total land holdings or the value was missing. In the first case, it is impossible to disentangle whether they sum to more than total land holdings because of mixed farming or because of reporting error. We thus focus instead on the incidence of diversification.

1 crop, while only 43.9% plant more than 1 variety of the main crop (see Table 2).

4.3 Are the Main Crops 'Safe'?

Most farmers (80%) plant potato and maize as their main crop, which are relatively safe. Another 8.6% plant other main crops which are native to the region (e.g. quinoa, yucca and grass). First, because these crops are endemic to the Andean region, farmers have generations' worth of experience and knowledge about these crops. For instance, potatoes have been cultivated in the Andes for about 8,000 years, tend to be resistant to cold weather and to a number of diseases and pests (National Research Council, 1989; Horton, 1983 and Carney, 1980). This resistance is strongest among the traditional (or native) potato varieties. About 90% of our sampled potato farmers report using traditional varieties. Furthermore, the Mantaro river valley is particularly ideal for growing both potato and maize because of its low risk of frost (Hastorf, 2001) and the lower-lying regions in the valley provide adequate climate for maize (Antezana et al., 2005). These factors contribute to potatoes and maize displaying relatively low yield fluctuations and thus relatively low yield risk. Indeed, annual data at the regional level shows that the coefficient of variation of potato and maize over the period spanning 1950 to 2004 is lower than less endemic crops such as wheat and beans.

Second, because of a high local demand for both potatoes and maize, there is little risk that farmers will not find a market to sell their product, and because most of these crops are sold on local markets (Horton, 1983), they are not subject to larger world price fluctuations. In fact, subsistence producers typically produce traditional potatoes for their home consumption, and certain types of bitter potatoes are processed into *chuño*, which can be stored for years and 'provides households with a degree of food security in this highly uncertain environment' (Horton, 1983). Since both yield and price risk seem relatively low, that potato and maize are relatively safe crops is a reasonable assumption in our sample.

4.4 Explanatory variables generated by the experiment

The explanatory variables generated by the risk and ambiguity measures are rank orderings, where risk and ambiguity aversion are increasing in the ranking.[12] Our measure of risk aversion (RA) is simply the number of times a subject chooses the safer of the two lotteries in her choice set. The measure is thus increasing in risk aversion. It is presented in the second column of Table 3, labeled 'Risk aversion'. It is identical to the one used by Holt and Laury (2002). For intuition behind the measure, notice that as an expected utility maximizer moves down the rows of Figure 2, once she chooses the riskier of the two lotteries, she should choose the safer of the two in all subsequent rows. For example, if a subject chooses the riskier lottery in row 1, then this lottery becomes the safer lottery in row 2. Since she has already revealed her maximum acceptable risk level in row 2, all subsequent row choices should be safe. The more safe choices she makes, the more risk averse she is.

Our measure of ambiguity aversion (AA) uses the number of times a subjects pays to avoid the ambiguous gamble. The measure is thus increasing in ambiguity aversion. The measure is more complicated than the risk aversion measure because revealed ambiguity preferences are conditional on risk preferences. This can be seen in Equation (2), where, in order to take an expectation over all possible probability distributions of gambles, it is necessary to know the expected utility of each gamble. Thus the ambiguity measure will take the form of a two-dimensional table, with number of safe choices on one dimension, and number of times paid to avoid ambiguity in the other dimension.

To generate the ambiguity ranking, we first computed an interval estimate of the CARA utility function $U(x) = -\frac{1}{\rho} \exp -\rho x$ for each number of safe gambles chosen in the risk instrument. We then used the midpoints of these intervals to compute the midpoints of an ambiguity parameter, for each number of times a subject paid to avoid ambiguity, using the same CARA utility function $v(x) = -\frac{1}{\tau} \exp -\tau x$. The CARA utility function, for which the

[12] Engle-Warnick and Laszlo (2008) introduce and detail the construction of these measures.

index of risk aversion depends on wealth levels, is acceptable for this application because we are interested in the relative ranking of the preference represented by the subjects choices, not in the value of the utility function parameter itself. These rank orderings are presented in the right-hand portion of Table 3 labeled 'Ambiguity Aversion'.The results from our experiment are shown in Figures 5, 6 and 7 and display a significant amount of response heterogeneity.

4.5 Explanatory variables generated by the survey

Our survey includes a number of questions that allow us to control for a number of demographic, socio-economic and agricultual characteristics. The average participant in the experiment is about 43 years old, most likely the head of the household, married and is almost equally likely to be male or female. Educational attainment is very heterogeneous with just over a quarter of the sample having attained less than completed primary school, over one third having completed primary but attained less than completed secondary, and 14.7% having some post-secondary schooling. Math skills, as measured by the math index, are weak, with the average subject giving less than one correct answer out of three.[13]

While our survey does not include information about income or consumption, we control for wealth in two ways. First, we construct an 'Unmet Basic Needs Index' (UNBI) to approximate a farmer's poverty status. We follow the Peruvian Statistical Agency's formula for the UBNI which takes into account the materials used in the construction of the dwelling walls, floors and roofs, and whether the dwelling has electricity, running water and sanitation. The higher the UBNI, the poorer the farmer. Second, all individuals in the sample hold some land (75% own, the rest rent). These land holdings are nonetheless small, as the average is at just under 2 hectares (there is one outlier at 15 hectares).

Subjects on average have just over 12 years of experience with the main crop and just over 9 years experience with the main variety of the main crop. Only 30% of the sample

[13] Subjects were asked simple algebra questions: $7 \times 3 - 4 = ?$; $12 \times 2 - 0.5 = ?$; and $31 \div 2 = ?$. The math index simply counts the number of correct answers. It is strongly correlated with educational attainment.

has received technical assistance. The average time to reach the nearest agricultural extension services or credit office is about three quarters of an hour. However, underlying these statistics are differences across the Costa and Sierra sub-samples. Because these two regions are geographically and ecologically very different, access to markets and services are very different. Indeed, technical assistance is more frequent among Costa farmers than Sierra farmers, and their access to agricultural extension and credit services are also far better. Because of these regional differences, we include session controls in our analysis.

5 Results

5.1 Risk and Ambiguity Aversion Measures

Before analyzing the effects of our behavioral measures on farmers' decisions, we begin by discussing how they correlate with the observable socio-economic characteristics. Specifically, for each behavioral measure (RA and AA), we estimate:

$$Y_i = \mathbf{X_i'}\beta_1 + \mathbf{Z_i'}\beta_2 + \epsilon_i \tag{3}$$

where Y_i is RA or AA, $\mathbf{X_i}$ is a vector of respondent characteristics (e.g. demographics and education), $\mathbf{Z_i}$ is a vector of household, farm and regional controls, and ϵ_i is a stochastic disturbance term. We estimate the regressions using an ordered probit.

The first column of Table 4 presents the correlates for our measure of risk aversion and the second column presents the results for our measure of ambiguity aversion. The only strongly significant predictor of either measure is household size: farmers from larger households are less ambiguity averse. The relationship between household size and risk aversion is a common finding in the empirical literature on risk aversion.[14] The UNBI predicts risk aversion: poorer

[14] Galor and Michalopoulos (2006) derive an evolutionary model of economic development which highlights the role that risk aversion plays in both fertility and innovation decisions. The result in Table 4 suggests that ambiguity aversion may also be affected by household size.

farmers are more risk averse, consistent with the concept of relative risk aversion.

5.2 Regression Results

To analyze the effect of RA and AA on diversification, we estimate the following:

$$D_i = \alpha_1 RA_i + \alpha_2 AA_i + \mathbf{X_i'}\gamma_1 + \mathbf{Z_i'}\gamma_2 + \eta_i \tag{4}$$

where D_i is either whether the farmer diversifies across crops or whether the farmer diversifies across varieties for the main crop, $\mathbf{X_i'}$ is a vector of variables including respondent characteristics (e.g. demographics and education), $\mathbf{Z_i'}$ includes household, farm and regional controls and η_i is a stochastic disturbance term.

The theory predicts that both risk and ambiguity aversion decrease diversification away from the safe options. We do not observe the share of land dedicated to the safe versus the risky crops – that is, we cannot relate our measures of risk ambiguity aversion to the extent of diversification. As the dependent variable reflects the incidence of diversification, our model predicts that risk and ambiguity aversion both reduce the probability of diversification. Table 5 shows the results for crop diversification (columns (1) to (3)) and for variety diversification (columns (4) to (6)). Because of the dichotomous nature of the dependent variables, the results are estimated using the probit model, and the table presents the marginal effects from this estimation, evaluated at the means of the independent variables.

Risk aversion statistically significantly predicts whether a farmer diversifies across crops: the more risk averse the farmer is, the less likely she is to plant more than one crop. While a risk averse farmer should hold positive amounts of both risky and safe crops, this result may seem at first counter-intuitive. Specifically, this ought to be true only in the instances where the expected yields of all crops are the same (which is unlikely the case) or when the farmer is infinitely risk averse. In the case that the farmer is infinitely risk averse, the theory predicts that she will only plant the safe crop. For the result in Table 5 to be consistent with the model of diversification, it would have to be the case that our results are driven by the most risk averse subjects. When we remove the most risk averse subjects (namely those that chose the safe gamble at least three times, accounting for about 40% of our sample), the coefficient of risk aversion becomes statistically insignificant.[15]

If we consider ambiguity rather than risk aversion, we find a similar result (column (2)): ambiguity aversion reduces the probability that farmers diversify away from the safe crop. Including both measures in the regression (column (3)), both coefficients become insignificant, though an F-test finds that they are jointly significant at 10%. The results for variety diversification are quite different: risk aversion is statistically insignificant, but ambiguity aversion strongly negatively predicts diversification across varieties of the main crop. This effect persists when both measures are included in the regression (column (6)).[16]

The effect of risk aversion on crop diversification can be explained by the theoretical prediction from the model that risk averse individuals hold an increasing share of their portfolio in safe crops. Because most main crops planted by our sample of farmers are endemic to the region, have relatively low yield variance and are subject to fewer demand shocks, this supports our model. While risk aversion does not appear to affect varietal diversification, ambiguity aversion does. This result suggests that there is something ambiguous about the outcomes of the main varieties of the main crop: for instance farmers might not have much information about yield or price distributions of some varieties of the main crop.

This makes sense if we think of farmers trying new varieties: they tend not to know as much about their yield distributions. Indeed, the survey also asked whether any of the top three varieties are new to the farmer. While only 16% responded that one of the top three

[15] Regression results available from the authors upon request. This finding suggests an avenue of future research, which is to explore the behavior of strongly risk averse individuals. Engle-Warnick and Laszlo (2008) find a similar result.

[16] Because the ambiguity aversion measure incorporates risk aversion, as dictated by the theory, it is possible that the results in column (3) are picking up some multi-collinearity. However, a number of checks (such as variance inflation factors, condition indices and eigen-values) between these two variables fail to find cause to worry about multi-collinearity.

varieties is new to them, only 9% of those who planted only one variety of the main crop said the variety was new to them. In contrast, of the farmers who planted more than one variety, 26% responded that one of the varieties was new to them.[17]

This point is perhaps best illustrated with anecdotal evidence. At the time of our field work, a local non-profit organization in the Mantaro valley had been trying to convince local farmers to plant a potato variety (*Capiro*), which has been successful in other regions of the Peruvian Sierra. Because of its adaptability to deep-frying, which is not the case of local varieties, the *Capiro* variety is attractive to potato chip distributors such as Frito Lays. However, farmers were reluctant to adopt it until they could observe other farmers' experience with it. In other words, their lack of experience with this variety's performance (despite successful adoption in other regions and good performance in field trials), specifically uncertainty about its yield distribution, contributed to slow diffusion in the community.[18]

Table 5 suggests that both risk aversion and ambiguity aversion affect the farmer's portfolio choice. The fact that these behavioral parameters actually predict farm choices implies that markets are not perfect or complete and that farmers are not able to contend *ex post* with risk in this region. Indeed, rural Peru is known to have imperfect credit and insurance market (Guirkinger and Boucher, 2008), and the descriptive statistics suggest that it can take up to three hours to even reach the nearest credit office. We include this measure of access to formal credit (time to reach the nearest credit office) in our regressions, and we find that it is negatively associated with the probability that a farmer diversifies. Because this is a weak proxy for access to credit (even if they are close to a credit office, they may not have access to credit because of informational asymmetries and lack of collateral), the estimated coefficient likely underestimates the true effect of credit constraint.

Our results also suggest that learning-by-doing is important in determining portfolio

[17] The sample of those who plant a new variety is too small to conduct any meaningful analysis.

[18] This anecdote comes from discussions with Ing. Walter León Robles, the Mantaro Office Director of FOVIDA (a well respected local NGO providing technical assistance and agricultural extension services to local producers).

choice. Specifically, the more experienced a farmer is with planting the main crop, the more likely she plants more than one variety. This result is consistent with Conley and Udry (2008) and Engle-Warnick and Laszlo (2008) who emphasize the importance of learning-by-doing in the adoption of new technologies.

5.3 Robustness Checks

The results of our analysis rest on two assumptions. The first assumption is that the subjects understood the experiment. Second, that our dependent variables measure diversification away from the safe crop or variety. This subsection explores both in more depth.

We conduct robustness checks by using the number of times subjects chose payoff-dominated alternatives (recall Figure 4). The distribution of the number of payoff dominated choices (out of a maximum of five) is displayed in Figure 8. Confirming findings in Engle-Warnick et al. (2009), Peruvian farmers do indeed reveal a non-negligible preference for payoff dominated alternatives. In an unreported regression paralleling that in Table 4 for the other two behavioral measures, we find that age and performance on the math tests significantly predicted the number of payoff-dominated choices.

If this preference for payoff-dominated alternatives matters for decision-making, we might expect that it also predicts portfolio choice. We begin by including in regression (4) our measure of payoff-dominated preference. The results can be found in panel A of Table 6. The coefficients on risk and ambiguity aversion are within one standard deviation of the results in Table 5. The preference for dominated alternatives only statistically significantly predicts portfolio choice at the 10% level in four of the six specifications. The main conclusions from Table 5 remain: risk and ambiguity aversion predict diversification across crops, while ambiguity aversion alone significantly predicts varietal diversification.

Panel B of Table 6 considers only subjects who chose fewer than four dominated choices.[19]

[19] Considering those who chose the dominated alternative fewer than once reduces the sample size so much

The main results from Table 5 are robust to this sample restriction. Specifically, risk and ambiguity aversion (though more weakly so) predict diversification across crops, while ambiguity aversion and not risk aversion predicts diversification across varieties. In fact, the estimated effect of ambiguity aversion on variety diversification becomes even more strongly negative with this sample restriction, indicating that the results we find here might be a lower bound estimate of the effect of ambiguity aversion on portfolio choice.

We pursue the possibility that respondents might not have understood the experiment very well by restricting the sample by age (since we found that the older subjects were more likely to choose dominated alternatives, and are the ones most likely to not understand the experiment due to their low levels of education). In Panel C of Table 6, we exclude subjects aged 60 and above. The results that we found in Table 5 are again robust to this sample restriction, and the magnitudes are greater indicating stronger effects: risk aversion predicts crop diversification and ambiguity aversion predicts variety diversification.

In summary, we have attempted to rule out that the patterns that we found in Table 5 were driven by subjects' inability to understand the experiment. We utilized two proxies of this inability, one of which is a measure generated by our experiment: preferences for dominated alternatives and age. The robustness analysis conducted here does not force us to overturn our main results.

Finally, our interpretation rests upon the assumption that most of the main crops planted by our subjects are relatively safe because they are endemic to the region. To test this, we restrict the sample of farmers who plant main crops which we know are endemic: potatoes, corn, yucca, quinoa and grass. Doing so reduces the sample by only 10 subjects. The results, presented in Panel D of Table 6, are very similar to our main results in Table 5: risk aversion predicts crop diversification, and ambiguity aversion predicts varietal diversification. Interestingly, the effect of ambiguity aversion on crop decisions gets wiped out: farmers have

that the regressions become insignificant.

more experience with native crops, and so have more information about their performance, and unknown-probabilities should indeed be less of an issue in this case.

6 Conclusion

In this paper, we argue that both ambiguity and risk aversion are important in understanding farmers' decision-making under uncertainty. In an environment where *ex-post* risk management mechanisms are weak because of imperfect or incomplete credit and insurance markets, farmers must undertake *ex-ante* mechanisms such as crop or varietal diversification which rely on often unknown outcome probability distributions. We adapt a standard model of portfolio choice to the case where the probability of good yield is unknown. We find that farmers' attitudes towards ambiguity reduce the likelihood that they plant more than one variety of their main crop, while their attitude towards risk seems to have little to no measurable effect on this decision.

Our findings contribute to the literature on decision-making under uncertainty in developing countries by showing that ambiguity aversion, not just risk aversion, is critical in farmers' decisions. This is a particularly salient point given that farmers must choose among technologies whose underlying yield distributions are unknown, and this is particularly true of new technologies. In addition, our results provide policy makers with a useful tool to mitigate the negative effects of uncertainty in a poor agricultural society. If risk aversion matters, little can be done other than helping the poor access *ex-post* risk management mechanisms. Such mechanisms are difficult to employ where people are poor, have little collateral and where asymmetric information exists. If ambiguity aversion matters, then policy makers can target their interventions at helping the poor resolve uncertainty about the crops and varieties they use, through agricultural research and extension services.

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Table 1: Preference Parameter Rankings

Risk aversion		Ambiguity aversion					
# Safe choices		# of Times Paid to Avoid Ambiguity					
		0	1 (2/62)	2 (8/53)	3 (14/44)	4 (20/35)	5 (26/26)
4	4	0	10	11	13	13	13
3	3	0	5	7	11	12	13
2	2	0	3	4	8	10	13
1	1	0	1	2	6	9	13
0	0	0	0	0.5	2	4	13

note: this is the table of rankings of measures, with 0 being least averse on both measures

Table 2 - Descriptive statistics (N=136)

Variable	Mean	Std. Dev.	Min	Max
Diversifies crops	0.676	0.470	0	1
Diversifies varieties	0.426	0.496	0	1
Age	43.316	14.270	18	78
Household Head	0.757	0.430	0	1
Male	0.559	0.498	0	1
Married	0.735	0.443	0	1
Separated	0.140	0.348	0	1
Single	0.125	0.332	0	1
Less than completed primary	0.272	0.447	0	1
Primary, less than completed secondary	0.375	0.486	0	1
Secondary completed	0.206	0.406	0	1
Post-secondary schooling	0.147	0.355	0	1
Math Index	0.941	1.024	0	3
Household Size	5.412	2.216	1	14
Unmet Basic Needs Index	0.407	0.208	0	0.917
Time to nearest agricultural extension services	44.471	31.176	2	180
Time to reach nearest credit office	47.522	30.908	5	180
Coast	0.257	0.439	0	1
Landsize (Ha)	1.973	1.981	0.025	15
Land is irrigated	0.706	0.457	0	1
Years of experience with the main crop	12.423	11.603	1	60
Received technical assistance with the main crop	0.301	0.461	0	1

Table 3: Comparative Statics of Risk and Ambiguity Preferences

		Share of Asset							
Parameter		Risky Only		Amb. Only		Risky and Ambiguous			
Risky	Amb.	Safe	Risky	Safe	Amb.	Safe	Amb.	Risky	Risky/Amb.
1	0.1	0.9753	0.0247	0.987	0.013	0.971	0.010	0.019	1.900
0.5	0.1	0.9459	0.0541	0.973	0.027	0.939	0.020	0.041	2.050
0.1	0.1	0.7297	0.2703	0.871	0.129	0.697	0.097	0.206	2.124
0.1	1	-	-	0.909	0.091	0.708	0.066	0.226	3.424
0.1	2	-	-	0.931	0.069	0.714	0.048	0.238	4.958
0.1	3	-	-	0.945	0.055	0.717	0.039	0.244	6.256

Safe Asset: 26 S/.; Risky Asset: 50/50 chance of 20 S/.or 35 S/.; Amb Asset: 14 S/. or 44 S/.

Table 4 - Determinants of Risk and Ambiguity Aversion

	Risk aversion	Ambiguity aversion
Age	-0.007	0.006
	(0.011)	(0.010)
Household Head	-0.091	-0.115
	(0.298)	(0.261)
Male	0.333	0.156
	(0.281)	(0.220)
Married	-0.468	-0.022
	(0.348)	(0.333)
Separated	-0.189	0.050
	(0.439)	(0.444)
Household Size	-0.084	-0.143
	(0.053)	(0.042)***
Primary, less than secondary completed	0.607	0.345
	(0.444)	(0.432)

Table 4 continued next page…

Table 4 (Continued) - Determinants of Risk and Ambiguity Aversion

	Risk aversion	Ambiguity aversion
Secondary completed	0.513	0.232
	(0.503)	(0.464)
Some post-secondary	0.903	0.532
	(0.606)	(0.607)
Math index	0.132	-0.183
	(0.121)	(0.122)
Landsize	0.048	-0.021
	(0.046)	(0.061)
Land is irrigated	-0.158	-0.050
	(0.280)	(0.251)
Unmet basic needs index	1.771	0.553
	(1.023)*	(0.982)
Time to nearest agricultural extension services	-0.002	-0.003
	(0.005)	(0.004)
Time to reach nearest credit office	0.002	0.002
	(0.005)	(0.005)
Main crop is corn	-0.001	-0.146
	(0.377)	(0.328)
Main crop is potato	-0.211	-0.301
	(0.357)	(0.363)
Years Experience with the main crop	-0.007	0.009
	(0.013)	(0.012)
Received technical assistance for the main crop	0.167	0.195
	(0.307)	(0.297)
Wald Chi-Squared	54.16***	40.77**
Pseudo R-Squared	0.0908	0.0395

*, **, *** significant at 10%, 5% and 1%. Robust standard errors in parentheses. N=136

Table 5 - Probit Marginal Effects

	Diversify Crops			Diversify Varieties		
	(1)	(2)	(3)	(4)	(5)	(6)
Risk aversion	-0.053		-0.021	-0.069		-0.015
	(0.028)**		(0.024)	(0.052)		(0.057)
Ambiguity Aversion		-0.015	-0.012		-0.036	-0.038
		(0.007)**	(0.007)		(0.012)***	(0.013)***
Primary, less than completed secondary	0.414	0.337	0.360	0.339	0.351	0.345
	(0.149)***	(0.0144)**	(0.149)***	(0.258)	(0.263)	(0.268)
Secondary completed	0.206	0.156	0.166	0.507	0.499	0.491
	(0.074)**	(0.068)**	(0.070)**	(0.224)*	(0.230)*	(0.238)*
Post secondary	0.176	0.159	0.159	0.395	0.489	0.483
	(0.064)**	(0.064)**	(0.063)**	(0.310)	(0.280)	(0.290)
Math index	0.028	0.016	0.020	0.128	0.072	0.069
	(0.039)	(0.036)	(0.037)	(0.079)*	(0.078)	(0.080)
Size of land holdings	0.189	0.158	0.164	0.199	0.185	0.183
	(0.046)***	(0.046)***	(0.047)***	(0.064)***	(0.061)***	(0.061)***
Land is irrigated	0.076	0.061	0.065	-0.056	-0.118	-0.122
	(0.100)	(0.086)	(0.086)	(0.209)	(0.218)	(0.215)

Table 5 continued next page…

*, **, *** significant at 10%; 5%; 1%. Robust standard errors in brackets. All regressions include demographics (age, gender, household head, marital status) and session controls. Omitted category for education: less than primary. N=136

Table 5 (continued)- Probit Marginal Effects

Unmet Basic Needs Index	1.098	0.832	0.892	1.288	1.329	1.319
	(0.394)***	(0.341)***	(0.360)***	(0.715)*	(0.716)*	(0.725)*
Time to nearest agricultural extension services	0.000	0.000	0.000	0.002	0.002	0.001
	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Time to nearest credit office	-0.004	-0.004	-0.004	-0.004	-0.003	-0.003
	(0.002)**	(0.002)***	(0.002)***	(0.003)	(0.003)	(0.003)
Main crop is corn	0.044	0.050	0.047	0.092	0.004	0.001
	(0.067)	(0.059)	(0.058)	(0.215)	(0.214)	(0.214)
Main crop is potato	0.105	0.123	0.115	0.325	0.278	0.279
	(0.078)	(0.081)	(0.077)	(0.176)*	(0.192)	(0.190)
Years experience with the main crop	0.008	0.006	0.006	0.011	0.018	0.019
	(0.006)	(0.005)	(0.005)	(0.008)	(0.008)**	(0.008)**
Received technical assistance with main crop	0.024	0.029	0.028	0.302	0.004	0.280
	(0.080)	(0.061)	(0.063)	(0.212)	(0.009)	(0.211)
Years experience with the main variety				0.008	0.282	0.003
				(0.009)	(0.211)	(0.009)
F-test for joint significance of both measures			5.63*			9.43***
Wald Chi-Squared	85.38***	78.10***	52.06***	88.73***	86.16***	88.17***
Pseudo R-Squared	0.5603	0.5704	0.5735	0.5071	0.5330	0.5332

*, **, *** significant at 10%; 5%; 1%. Robust standard errors in brackets. All regressions include demographics (age, gender, household head, marital status) and session controls. Omitted category for education: less than primary. N=136

Table 6 - Robustness Analysis (Probit Marginal Effects)

Dependent Variable	**Diversifies Crops**			**Diversifies across Varieties**		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Including dominated choices in binary dominated gamble (N=136)						
Risk aversion	-0.056		-0.026	-0.670		0.007
	(0.026)**		(0.022)	(0.052)		(0.058)
Ambiguity aversion		-0.014	-0.010		-0.033	-0.034
		(0.006)**	(0.007)		(0.011)***	(0.013)***
Dominated choice	-0.045	-0.035	-0.038	-0.077	-0.051	-0.050
	(0.025)*	(0.023)*	(0.023)*	(0.046)*	(0.046)	(0.046)
F-test for joint significance			7.51**			8.72**
Wald Chi-Squared	80.53***	73.07***	75.68***	89.14***	91.35***	63.10***
Pseudo R-Squared	0.5751	0.5820	0.5877	0.5182	0.5374	0.5374
Panel B - Excluding subjects who chose more than 3 dominated choices in the binary dominated gamble (N=116)						
Risk aversion	-0.045		-0.022	-0.061		0.042
	(0.027)**		(0.023)	(0.061)		(0.070)
Ambiguity aversion		-0.011	-0.008		-0.043	-0.049
		(0.007)*	(0.007)		(0.016)***	(0.019)***
F-test for joint significance			5.21*			7.33**
Wald Chi-Squared	55.94***	57.73***	58.71***	106.00***	93.49***	90.68***
Pseudo R-Squared	0.5523	0.5568	0.5617	0.5659	0.5925	0.5938

Table 6 Continued Next Page...

Table 6 (Continued) - Robustness Analysis (Probit Marginal Effects)

Dependent Variable	Diversifies Crops			Diversifies across Varieties		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C - Excluding subjects who are above 60 years old (N=119)						
Risk aversion	-0.081		-0.035	-0.084		0.049
	(0.042)**		(0.038)	(0.059)		(0.070)
Ambiguity aversion		-0.022	-0.018		-0.074	-0.084
		(0.010)**	(0.011)		(0.019)***	(0.023)***
F-test for joint significance			5.44*			14.36***
Wald Chi-Squared	77.88***	67.04***	73.46***	114.75***	99.31***	97.32***
Pseudo R-Squared	0.5214	0.5322	0.5356	0.5603	0.6124	0.6141
Panel D - Including only observations if main crop is endemic (N126)						
Risk aversion	-0.038		-0.031	-0.088		0.000
	(0.026)***		(0.024)	(0.059)		(0.070)
Ambiguity aversion		-0.008	-0.003		-0.033	-0.034
		(0.006)	(0.005)		(0.014)**	(0.016)**
F-test for joint significance			4.64*			6.27**
Wald Chi-Squared	53.49***	48.69***	54.23***	82.57***	79.76***	86.27***
Pseudo R-Squared	0.5870	0.5778	0.5884	0.5318	0.5481	0.5481

Robust standard errors in parentheses. *, **, *** significant at 10%; 5%; 1%. All regressions include the Table 5 controls.

Figure 1: ‘Five Options’ Risk Preference Measurement Instrument

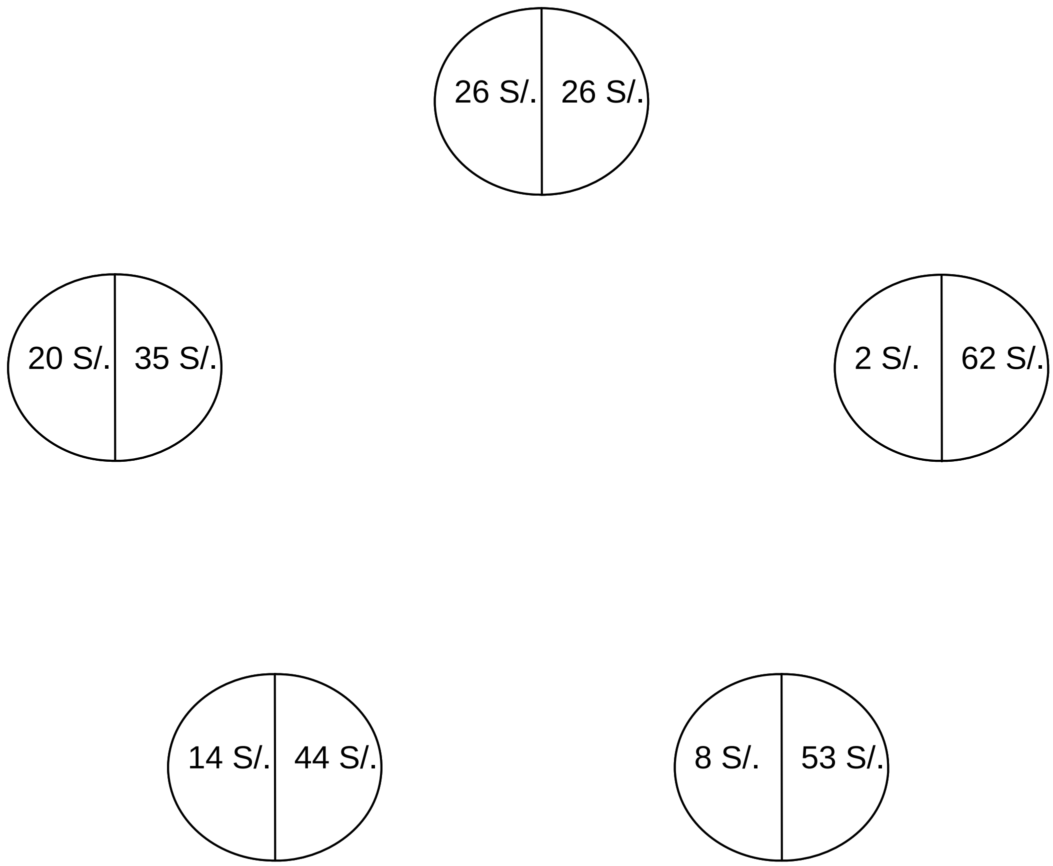

Figure 2: Decomposing the 'Five Options' Instrument into a Series of 'Binary Options' Instruments

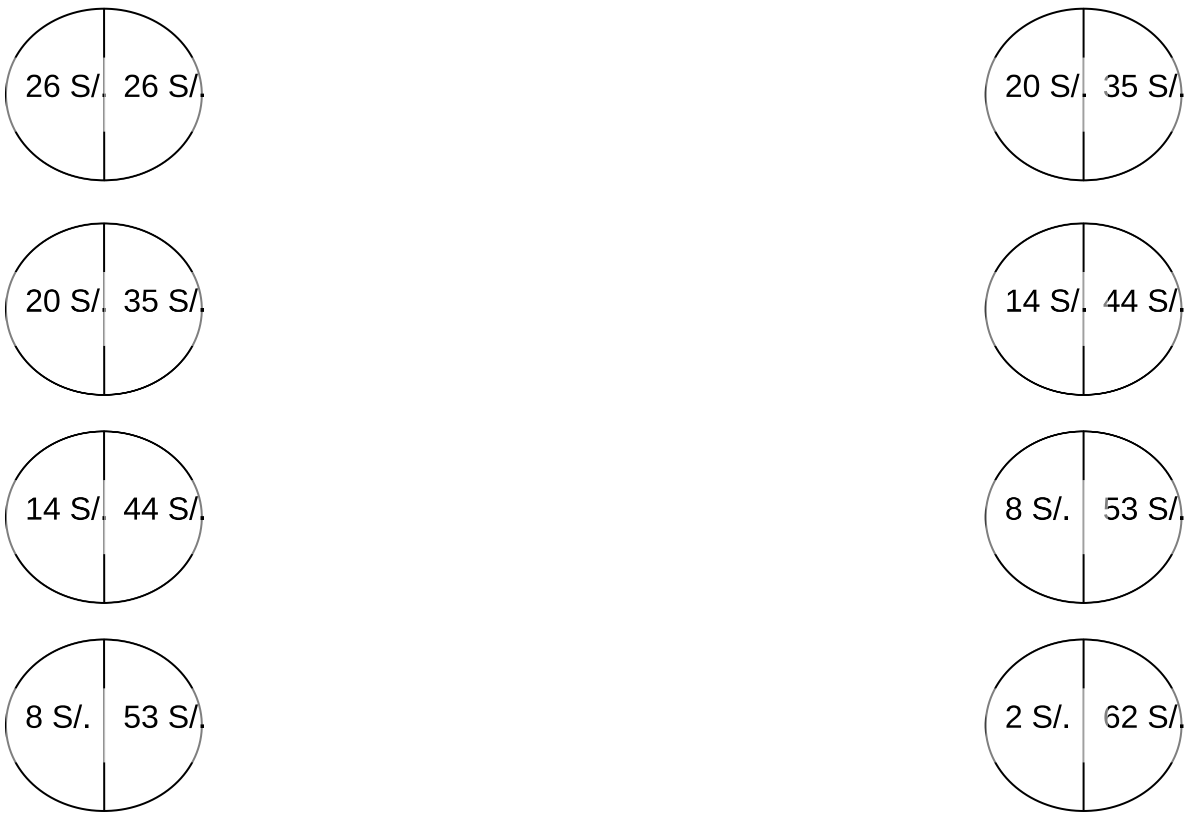

Figure 3: Binary Choices to Reveal Preferences for Ambiguity

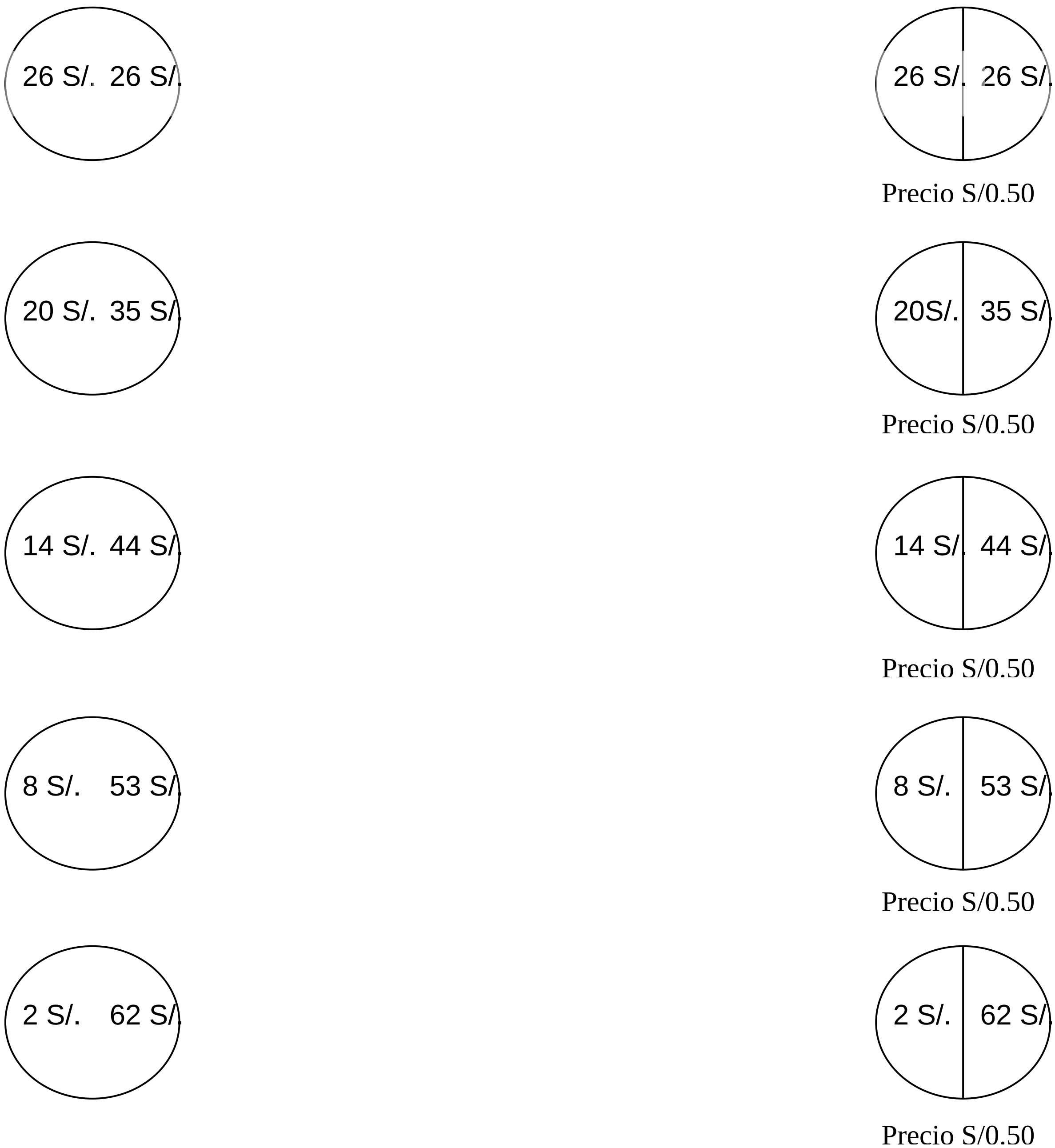

Figure 4: Binary Choices to Reveal Preferences for Dominated Alternatives

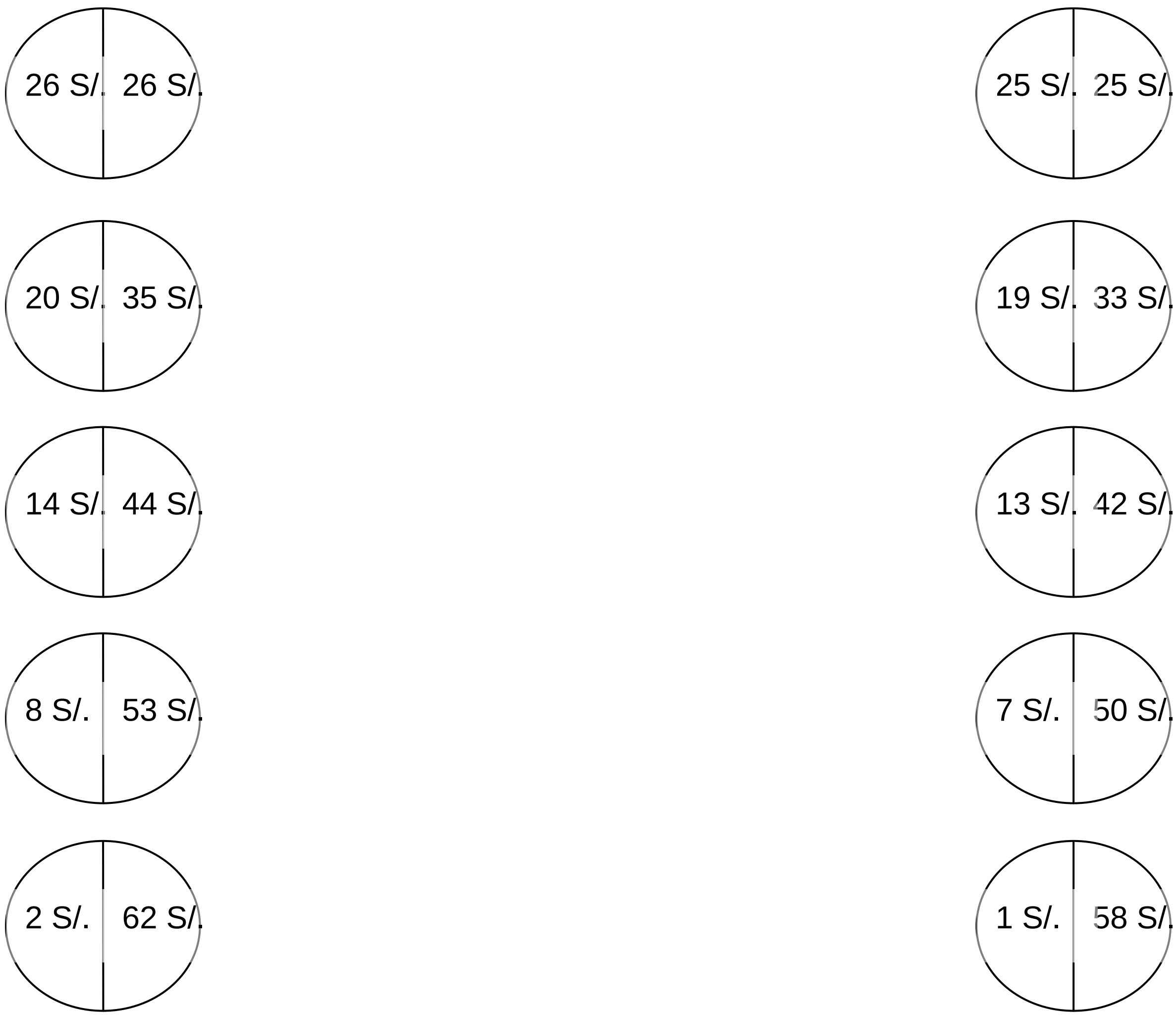

Figure 5 - Risk Aversion

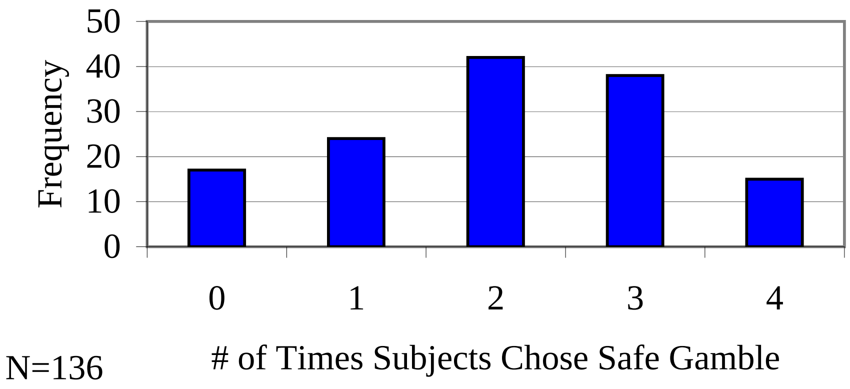

Figure 6 - Ambiguity Aversion

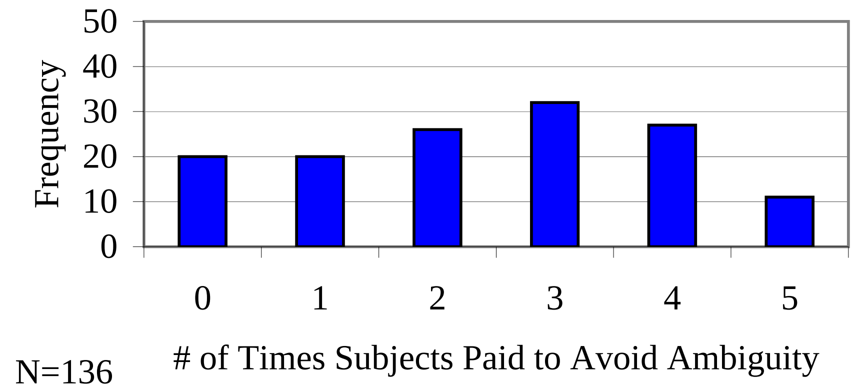

Figure 7 - Ranked Amb. Aversion Measure

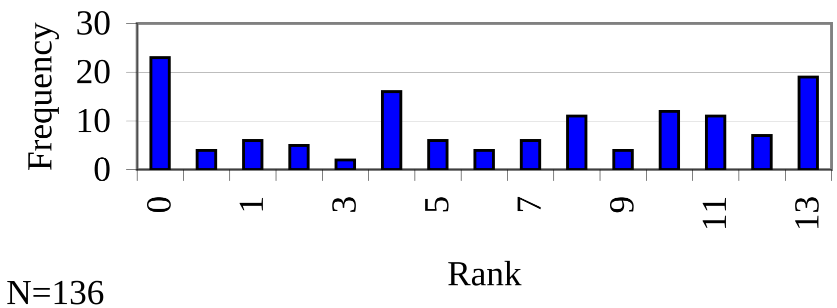

Figure 8 - Dominance Preference