Is Risk Aversion Really Correlated with Wealth?

How estimated probabilities introduce spurious correlation

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May 2006

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, California, July 23-26, 2006

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ABSTRACT

Economists attribute many common behaviors to risk aversion and frequently focus on how wealth moderates risk preferences. This paper highlights a problem associated with empirical tests of the relationship between wealth and risk aversion that can arise when the probabilities individuals face are unobservable to researchers. The common remedy for unobservable probabilities involves the estimation of probabilities in a profit or production that includes farmer, farm and agro-climatic variables. Unfortunately, these variables are often correlated with wealth such that estimated probabilities are likely to leave statistical fingerprints on subsequently-estimated risk aversion coefficients and may thereby introduce spurious correlations between wealth and risk preferences. In this paper, we use data from an experiment conducted among 290 Indian farmers to detect these spurious correlations. We estimate coefficients of risk aversion with known probabilities and with estimated probabilities and compare subsequent correlations with wealth and other farmer traits. We estimate 'unobservable' probabilities in conjunction with risk preferences following a standard field data approach. We explore the statistical implications of estimating probabilities by comparing correlations between wealth and these two sets of estimated risk preferences. These comparisons show how estimated probabilities can change risk aversion coefficients substantially and introduce spurious correlations between risk aversion and wealth.

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Economists attribute many common behaviors to risk aversion. These precautious behaviors often appear to be rational, but sometimes seem quite pernicious. Risk aversion, for example, is frequently blamed for poverty traps and impediments to technology adoption. Since responses to risk can be self-preserving in some settings and self-defeating in others, it is important to understand how individuals' degree of risk aversion shapes their decisions and outcomes. Beginning with the hypotheses proposed by Arrow (1971), pursuit of this understanding has focused largely on how wealth moderates an individual's risk aversion. Empirically testing the relationship between wealth and risk aversion is unfortunately plagued with a variety of problems. This paper highlights one such problem that arises when the probabilities individuals face when making a particular decision are unobservable, which is common in empirical settings.

To illustrate the inherent problems with relating risk aversion to wealth, suppose you wanted to estimate risk preferences among a group of farmers, then test for correlations between these estimated risk preferences and wealth and other farmer traits. You collect data on farmer characteristics and various farm management decisions and outcomes, and specify a utility function with estimable parameters that capture a measure of absolute or relative risk aversion. But now what do you use as probabilities when you estimate the implied expected utility model? Since you cannot observe probabilities associated with profit distributions in the field, you must estimate them instead, typically as a function of farmer, farm and agro-climatic variables. The analysis now gets complicated. Many of the factors affecting risk response also affect profit distributions and farm structure. This makes it difficult, if not impossible, to separate structural risk effects from behavioral effects, and severe bias can result from these confounding influences. Furthermore, variables used to estimate probabilities in the profit function potentially leave statistical fingerprints on estimated risk aversion coefficients in the utility function. This artifactual link between farmer traits and risk aversion coefficients renders any correlations between farmer characteristics such as wealth and risk preferences suspect. Simply put, you cannot tell whether the correlation is a meaningful result or a spurious artifact of the estimation procedure. Such a link may draw into question the now common tests of Arrows hypotheses relating risk to wealth.

In this paper, we use data from an experiment conducted among Indian farmers to detect these spurious correlations. Using known probabilities of experimental payoff distributions offered to farmers, we estimate farmers' revealed risk preferences and establish corresponding correlations with farmers' wealth. We then estimate revealed risk preferences under the assumption that farmers' decisions and outcomes are observable, but corresponding probabilities are not and must instead be estimated in conjunction with risk preferences as is commonly done with field data. By comparing correlations between wealth and these two sets of estimated risk preferences, we show how jointly estimating stochastic profit or production functions using farmer traits or other correlates of wealth changes risk aversion estimates substantially and clearly introduces spurious correlations between risk aversion coefficients and wealth.

1 BACKGROUND

Much early research on risk behavior considered how heterogeneity in risk aversion was related to socio-economic variables such as wealth or education (e.g., Friedman and Savage 1948). Arrow (1971) and Pratt (1964) developed coefficients of relative and absolute risk aversion for the purpose of objectively measuring aversion to risk. Arrow (1971) also proposed a series of hypotheses regarding how these measures relate to wealth. In particular, Arrow argued that individuals increase in relative risk aversion and decrease in absolute risk aversion as allocable wealth increases. Several empirical studies followed with the goal of testing Arrow's hypotheses.

Binswanger (1980) conducted some of the earliest tests of Arrow's hypotheses. Binswanger conducted experiments in India, asking individuals to choose to play one of eight gambles. The outcome of each gamble was determined by a coin toss. The gambles ranged from a safe amount of money (resulting from both heads and tails) to a 50% chance of a large gain and 50% chance of no gain. Each individual was asked to choose between the choices for several different payoff levels ranging from very small amounts, to more than the daily wage rate. No losses were possible. Binswanger associated a range of partial risk aversion with each choice, and then regressed these partial risk aversion measures on demographic variables for each level of payoffs. Binswanger finds some evidence that partial risk aversion declines with income and wealth (though insignificantly). Further, Binswanger finds little variation in risk aversion based on other socio-economic variables.

Other attempts to relate wealth or socio-economic data to risk aversion have depended on econometric estimation using data on investment or production decisions. Such econometric studies use either structural estimation based on a parametric utility model or reduced form estimation. Holt and Chavas (2001) outline many of the drawbacks of econometric estimation of risk aversion parameters and in particular of reduced form estimation. Reduced form estimation relies on estimating a Taylor series approximation of the expected utility function around the mean wealth level. This form has become popular because it is simple, and produces risk aversion coefficients that appear as simple linear coefficients of variance measures (e.g., Bar-Shira et al. 1997, Chavez and Holt 1990, Pope and Just 1991). Two primary drawbacks, noted by Holt and Chavas, to reduced form estimation are that (1) it can be difficult to infer how changes in socio-economic variables affect risk aversion measures, and (2) one must create some estimate of the individual's perceived risk from various choices. Estimating perceived risk may sound simple at first blush. However, one can never observe the moments of the distribution perceived *ex ante* by the decision-maker. Often econometric estimation will use outcomes to estimate *ex ante* beliefs. No matter what method is used, it is impossible to account for heterogeneity in risk perception by decision-makers. Unaccounted for, this heterogeneity of perception thus contaminates risk aversion estimates and possibly creates false correlations between socio-economic variables and risk parameters (Just 2001).

Holt and Chavas (2001) suggest that structural estimation is underutilized in measuring properties of risk aversion. Antle (1987), Chavas and Holt (1996), and Saha et al. (1994) each use a structural approach to measure risk parameters. Originally, employing a structural approach to test Arrows hypotheses was difficult because no functional form had been proposed that could satisfy the hypotheses. Saha's expo-power utility function (employed in Saha et al. to measure farmer's risk aversion) filled this gap by providing the necessary flexibility. While many have argued the benefits of structural estimation, results have been widely conflicting, and therefore suspect. Just and Peterson (2003) show that estimates of risk parameters fundamentally contradict the data that produced them. Using the conditional profit distribution estimated by Saha et al., Just and Peterson show that farmer's revealed preferences can only be consistent with a negatively sloped utility of wealth function and interpret this as evidence of the failures of expected utility theory. Just and Pope (2003) suggest that this contradiction may alternately be explained by the omission of heterogeneity in production technologies or external constraints on production in estimation. In many cases, heterogeneity in preferences and technology are confounded when both are estimated jointly. Even if estimated separately, it is difficult if not impossible to estimate a realistic conditional profit distribution – a prerequisite for using the structural approach in econometric estimation.

We overcome the inherent problems of estimation encountered in econometric studies of risk aversion by employing experiments. By using hypothetical seed distributions, we can control for the exact distribution of profits available to decision-makers. Moreover, by using willingness to pay data, we obtain much more detailed information on risk aversion parameters than was possible using Binswanger's dichotomous experimental design.

2 DATA

This paper uses data from the Salem and Perambalur districts of Tamil Nadu state, India (see Figure 1). These data were collected with local support from Tamil Nadu Agricultural University and funding from the Agricultural Biotechnology Support Program (USAID-Cornell University). Ten enumerators surveyed 290 households in three Perambalur villages (Annukur, Pandagapadi, and Namaiyur) and three Salem villages (Vellaiyur, Kilakku Raajapalayam, and Kavarparnai). These villages were selected from the 12 or so villages in Tamil Nadu that presently have more than 18 *Bt* cotton farmers.[1] The research team used choice-based stratified sampling to ensure the participation of *Bt* cotton farmers and other farmers. The team collected data in two parts. In the first part, enumerators administered a detailed household questionnaire focused on farmers' management decisions, valuation of seed traits, risk exposure and wealth. In the second part, the team conducted experiments with farmers to elicit their valuation of hypothetical yield distributions. Farmers earned money (Rupees (Rs)) according to their performance in the experiment.

The experiment consisted of a series of hypothetical farming seasons. At the beginning of each season, farmers were offered a 'seed' with a known Rupee-payoff distribution. This distribution was explained simply and repeatedly and shown graphically in order to facilitate

[1] One objective of the broader research project was to assess farmers' valuation of *Bt* crops (Lybbert forthcoming).

farmers' understanding of the payoff distribution implied by a given 'seed.' The distribution of a particular 'seed' was represented by 10 chips in a small black bag. There were three colors of chips, each representing a 'harvest' payoff: blue (high), white (average), and red (low). The distribution was modified by changing the proportion of blue, white and red chips in the bag. Farmers' valuation of the seed was elicited using an open-ended question, which generally elicits true values better than dichotomous choice questions (Balistreri et al. 2001, Coursey et al. 1999), and the well-known Becker-DeGroot-Marschak (BDM) mechanism (Becker et al. 1964). Before the price of the seed was known, each farmer expressed his maximum WTP for the seed. Following the BDM mechanism, the seed price was then randomly drawn from a uniform distribution with the minimum and maximum corresponding to the minimum and maximum Rupee-payoff. Farmers who were willing to pay at least as much as the randomly-drawn seed price 'purchased and planted' the seed.[2] With the help of a farmer, the lead enumerator would then draw a chip from the bag to determine the Rupee-payoff for the season. Farmers' season earnings were Rs50 plus their net seed earnings (harvest payoff minus the seed price). Farmers who did not 'purchase and plant' the seed because their WTP was lower than the seed price still received Rs50 at the season's end. Each seed and its corresponding yield distribution was offered for five consecutive seasons: four practice seasons, then one 'high-stakes' season. Practice season earnings were 'exchanged' for real Rupees at an exchange rate of 1/100. High-stakes season earnings were 'exchanged' at real Rupees with an exchange rate of 1/10.

The structure and presentation of the experiment was simplified as much as possible during pre-testing. As a necessary departure from the experimental economics principle of

[2] To make the BDM mechanism more tangible for farmers, the lead enumerator would explain that the mechanism worked much like sending money with a trusted friend to purchase the seed on their behalf without first knowing the seed price. If the friend had enough money with him to cover the seed price once he observed the price, he would purchase the seed and return any surplus money. If he did not have enough money to cover the seed price, he would not purchase the seed and return the money in full. This imagery effectively helped farmers to realize that it was in their best interest to send as much money as they thought the seed was worth, which is precisely the advantage of the BDM mechanism (Becker et al. 1964).

abstractness, the experiment was framed clearly in a farming context to improve farmers' understanding of the experiment. While all participants were farmers and abandoning some abstractness in favor of an agriculture context is therefore defensible, striking an appropriate balance between abstractness and context was challenging nonetheless. At the conclusion of the experiment, the enumerators asked farmers how well they had understood the experiment, to which 11% reported "with some confusion", 4% reported "poorly", and 0% reported "very poorly".

There were five payoff distributions in the experiment: a Base distribution (B), a High distribution (H), a Low distribution (L), a Stabilized distribution (S), and a Truncated distribution (T). To control for potential ordering effects, these five distributions were offered to farmers in one of four orderings: [B-S-T-H-L-B], [B-L-T-H-S-B], [B-T-L-S-H-B], and [B-H-S-L-T-B]. Since farmers' valuations of distribution changes are desired, all four orderings begin and end with the Base distribution, B, which we denote as B1 and B2, respectively.[3]

Figure 2 shows the marginal probability distributions for the payout distributions of the experiment along with the Expected Value (EV), standard deviation (σ) and skewness (sk) of each distribution. These simple typological distributions where chosen to facilitate farmers' understanding of the experiment. We used simple pictures like those in Figure 2 to capture each distribution and explain the experiment to farmers.

Table 1 contains descriptive statistics for several relevant variables from the questionnaire and experiment. Of the 290 farmers surveyed, only three (or 1%) are female. One third of the farmers have no formal education and the average farmer has five years. Subjects

[3] During the experiment, each enumerator worked separately with at most two farmers. If an enumerator was working with two farmers, they would be seated far enough apart that their conversations with the enumerator, including any questions about the experiment and the farmers' stated WTP, were completely private. Logistically, the experiment was typically held in a public room in the village and would last approximately two hours. The first hour was spent explaining and practicing the experiment, then tea was served and farmers could discuss the experiment among themselves. The second hour was spent on the B, H, L, S, and T distributions.

indicated that 33% (73%) own a television (radio), but only 4% own a tractor. Livestock are important for farmers in the survey area, and most farmers have at least a couple of animals.[4] The average farmer farms five or six acres, about a third of which is irrigated. Cotton and maize are the two most important crops in terms of the percentage of farmers' land planted. Farmers' top ranking management goal is, not surprisingly, increasing yield, after which come protecting against pest losses and lowering production costs. Stabilizing yield across years and increasing harvest quality are relatively less important to the average farmer. Most farmers earned more than Rs60 in the experiment and none earned less than Rs40. Compared to the daily wage for unskilled labor in the survey site of about Rs50 the experiment payoffs provided non-trivial incentives.

3 ESTIMATION

In this section, we describe two sets of estimation procedures. The first set uses farmers' willingness to pay (WTP) for experimental payout distributions to estimate coefficients of risk aversion. The second set of procedures uses these coefficients of risk aversion as dependent variables to estimate the relationship between risk aversion and farmer traits such as wealth and education. We present these sets of procedures along with estimation results in sub-sections A and B, respectively.

A. Coefficients of Risk Aversion

We use four different approaches to estimate coefficients of risk aversion. These four approaches all use farmers' WTP to estimate risk preferences, but differ in their treatment of the payout distribution probabilities. In particular, the *True Probabilities* approach assumes we know

[4] Tropical Livestock Units are constructed as a weighted sum of cows, bullocks and goats, where the weights are 1, 1 and 0.1, respectively.

the true underlying probabilities farmers faced when deciding on their WTP. Using these true probabilities we can solve directly for coefficients of risk aversion implied by farmers' WTP. The three other approaches, which we denote as *Estimated Probabilities* (*EP*) approaches, assume we do not know the true probabilities and must instead estimate them using *ex post* payout amounts. Probability estimation across these three approaches differs according to whether we can distinguish between the different seeds offered to farmers – i.e., whether we know which of the nine possible experimental payouts, {-30, 0, 20, 30, 50, 70, 80, 100, 130}, were relevant *ex ante* – and how we use this knowledge. Approaches *EP1* and *EP2* both assume we can distinguish between seeds. Approach *EP1* estimates probabilities separately for each seed. Approach *EP2* estimates probabilities by pooling all the *ex post* payout amounts and adding a dummy variable for each seed in this pooled equation. Approach *EP3* assumes we cannot distinguish between seeds and also estimates a pooled equation, this time without seed dummy variables. Each of these approaches – *EP1*, *EP2* and *EP3* – is designed to mimic procedures that are commonly employed in estimation with field data. We use estimates from the *True Probabilities* approach, which is the most efficient and least biased method of using the data to estimate risk preferences, as a benchmark for evaluating these *EP*-based estimates. We hope that the results from each method can tell us something of the nature and size of bias introduced by using estimated rather than true probabilities to infer how risk attitudes relate to other individual characteristics such as wealth.

True Probabilities Approach

In this straight-forward approach, we solve for the risk preferences implied by farmer *j*'s *WTP* for seed *t* using the expected utility relationship

Eq 1 $$U\left(w_j \mid \beta_{jt}\right) = \sum_i \pi_{it} U\left(w_j - WTP_{jt} + x_{it} \mid \beta_{jt}\right)$$

where U is the utility of wealth function, w_j represents wealth of individual j, β_{jt} is a risk aversion parameter for individual j and payout distribution t, π_{it} is the probability of outcome i in payout distribution t, and x_{it} is payout for outcome i in distribution t. The experiment described above provides data for variables π_{jt}, WTP_{jt}, and x_{it}; the companion questionnaire provides data for w_j. For any function U, then, we can solve for the risk aversion parameter β_{jt} that rationalizes farmer j's WTP_{jt}. This parameter simply adjusts the curvature of U to maintain the expected utility equality in Eq 1.

Before we specify a functional form for U, recall that each individual faced five different payout distributions. Under many circumstances, it would be possible to estimate a single risk aversion coefficient for each individual by minimizing squared error or by assuming a normally distributed error and maximizing the likelihood function. However, in the case of canonical risk aversion models with willingness-to-pay data, such estimators are biased even when distributions of the underlying uncertainty are known. Solving for β_{jt} separately for each observation t of individual j, then estimating $\bar{\beta}_j = \sum_t \beta_{jt} / T$ produces a consistent estimate of risk parameters (see Just and Lybbert 2005 for complete explanation).

We use a locally quadratic utility function to solve for individual risk preferences,

Eq 2 $$U(w) = 1 + \left(w_0 - w_1\right) - \beta\left(w_0 - w_1\right)^2$$

where β is the local Arrow-Pratt measure of absolute risk aversion, w_0 is initial wealth and w_1 is end-of-period wealth. We solve for seed-specific measures of absolute risk aversion for each individual, β_{jt}, by combining Eq 1 and Eq 2 and using the following expected utility relationship

Eq 3 $$1 = \sum_{i=1}^{3} \pi_{it} \left[1 + \left(-WTP_{jt} + x_{it} \right) - \beta_{jt} \left(-WTP_{jt} + x_{it} \right)^2 \right]$$

where payouts x_{it} are sorted for each seed t in ascending order: i={1=Low, 2=Mid, 3=High}.[5] Note that β_{jt} indicates the curvature required to maintain this expected utility relationship *for seed t* and is therefore a *seed-specific* coefficient of absolute risk aversion. We compute and analyze both β_{jt} and the average over all six seeds for each individual, denoted $\overline{\beta}_j$, then use these *True Probabilities*-based estimates as a benchmark for evaluating the *Estimated Probabilities* approaches.

Estimated Probabilities Approaches

In these approaches, we use the expected utility relationship in Eq 3 but assume we can no longer observe π_{it} and must estimate probabilities instead. With estimated probability p_{ijt} – which is specific to individual j if probabilities are conditioned by farmer traits such as education, land holdings, and wealth – the relationship in Eq 3 produces an *estimate* of the coefficient of risk aversion, b_{jt}, rather than the true implied coefficient β_{jt}. Before delving into different ways of estimating p_{ijt}, consider first the broader challenges of using field data to estimate risk preferences.

If we were using field data, rather than experimental data, we would still observe w, but field data analogues of WTP, π_{it} and x_{it} are more problematic. We could likely find a proxy for WTP. Although such a proxy might be more realistic than our experimental WTP, it would almost surely be less tidy and may even be binary (e.g., adoption of technique or technology). Our knowledge of the profit distribution facing individuals – the field data analogue of the

[5] There were a total of nine outcomes in the experiment: {-30,0,20,30,50,70,80,100,130}. Since each distribution had only three possible outcomes, the notation i={L,M,H} is used to denote the low, middle and high outcome for a given distribution and serves simply as a place holder for the numeric value of the outcome.

experimental payout distribution – would likely be even more garbled. We may or may not be able to distinguish clearly between the gambles (subscript *t*) relevant for each individual (e.g., crops, seed varieties, technologies, etc.). We would still observe the *ex post* outcome drawn by each individual, but may know very little about the size or number of outcomes the individual faced *ex ante*. The probabilities implicit in an individual's profit distribution would be even more difficult to observe. The next three approaches offer different ways of estimating these probabilities according to whether we can distinguish between and how we treat the seeds farmers faced in the experiment. We refer to these estimated probability approaches as *EP1: Known and Separate Seeds*, *EP2: Known and Pooled Seeds*, and *EP3: Unknown and Pooled Seeds*.

<u>*EP1: Known & Separate Seeds (KS)*</u>. In this approach, assume we know precisely which seed farmers faced when they formulated their *WTP* – i.e., we could see subscript *t* on *WTP* – and we can therefore estimate separate probability equations for each seed. This *Known and Separate Seeds* approach uses the observable *ex post* payouts corresponding to a given seed as the dependent variable and various farmer traits as the independent variables. We then use this estimated model to predict p_{ijt}^{KS}, the probability of each possible outcome *i* for seed *t* and farmer *j*. This approach is intended to mimic the common procedure of estimating profit distributions contingent on crop or other inputs, and then using this distribution to estimate risk preferences (e.g. Chavas and Holt, 1990).

Since the experiment offered farmers discrete payout distributions, we use an ordered probit model to estimate p_{ijt}^{KS} for *i*={1=L, 2=M, 3=H} and *t*=τ as follows

Eq 4

$$
\begin{aligned}
\tilde{x}_{j|t=\tau} &= \boldsymbol{\varphi}_{\boldsymbol{\tau}}^{\mathbf{KS}'}\mathbf{z}_{\mathbf{j}} + \varepsilon^{KS} \\
p_{L,j\tau}^{KS} &= \Phi\left(-\boldsymbol{\varphi}_{\boldsymbol{\tau}}^{\mathbf{KS}'}{}_{\tau}\mathbf{z}_{\mathbf{j}}\right) \\
p_{M,j\tau}^{KS} &= \Phi\left(\mu_{M\tau}^{KS} - \boldsymbol{\varphi}_{\boldsymbol{\tau}}^{\mathbf{KS}'}\mathbf{z}_{\mathbf{j}}\right) - \Phi\left(-\boldsymbol{\varphi}_{\boldsymbol{\tau}}^{\mathbf{KS}'}\mathbf{z}_{\mathbf{j}}\right) \\
p_{H,j\tau}^{KS} &= 1 - \Phi\left(\mu_{M\tau}^{KS} - \boldsymbol{\varphi}_{\boldsymbol{\tau}}^{\mathbf{KS}'}\mathbf{z}_{\mathbf{j}}\right)
\end{aligned}
$$

where $x_{j|t=\tau}$ is the observed payout for farmer *j* and seed τ, $\mathbf{z_j}$ is a column vector of traits for farmer *j* and $\boldsymbol{\varphi}_{\boldsymbol{\tau}}^{\mathbf{KS}}$ is a vector of estimable parameters for seed τ, ε^{KS} is an error term, $\mu_{M\tau}^{KS}$ is the estimated break between *i=L* and *i=M*, and Φ is the cumulative density function for the normal distribution. In estimating these probabilities, we specify a full model using the following farmer traits in the vector $\mathbf{z_j}$: age, education, a wealth index (discussed below), irrigated land holdings, and non-irrigated land holdings. To help identify the source of any spurious correlations between wealth and risk preferences in subsequent estimation, we also estimate probabilities excluding the wealth index from this trait vector and with a single random variable in place of this trait vector. We refer to these three specifications of the trait vector as the full, no wealth, and random variable specifications, respectively.

Estimating the ordered probit in Eq 4 is analogous to estimating a profit or production function assuming a (discrete) normal distribution of returns. Using these estimated probabilities with known and separate seeds, we then estimate a seed-specific coefficient of risk aversion for each farmer using the expected utility relationship in Eq 3, which we denote as b_{jt}^{KS}. This coefficient is directly comparable to the true coefficient β_{jt} as both are seed- and individual-specific. We also compute and analyze an average coefficient for each farmer, denoted $\overline{b}_{j}^{KS}$.

<u>*EP2: Known & Pooled Seeds (KP)*</u>. This approach still assumes we can distinguish between seeds, but estimates a single pooled equation for all eight seeds instead of treating each seed

separately. In this pooled equation we control for seed type using dummy variables. This approach is intended to mimic approaches that are similar to those above but allow less flexibility in the estimation of the distribution. In many cases, too little data exists to estimate full distributions for each input variety. In this case researchers will often introduce a dummy variable to control for variation. With the known seeds pooled in this way, probabilities for all nine possible payouts – p_{ijt}^{KP} for i={-30, 0, 20, 30, 50, 70, 80, 100, 130} – are predicted with a single estimated ordered probit model as follows

Eq 5

$$
\begin{aligned}
x_{jt} &= \boldsymbol{\varphi}^{\mathbf{KP}\prime}\mathbf{z_j} + \boldsymbol{\gamma}^{\mathbf{KP}\prime}\mathbf{t} + \varepsilon^{KP} \\
p_{-30,jt}^{KP} &= \Phi\left(-\left(\boldsymbol{\varphi}^{\mathbf{KP}\prime}\mathbf{z_j} + \boldsymbol{\gamma}^{\mathbf{KP}\prime}\mathbf{t}\right)\right) \\
p_{0,jt}^{KP} &= \Phi\left(\mu_0^{KP} - \left(\boldsymbol{\varphi}^{\mathbf{KP}\prime}\mathbf{z_j} + \boldsymbol{\gamma}^{\mathbf{KP}\prime}\mathbf{t}\right)\right) - \Phi\left(-\left(\boldsymbol{\varphi}^{\mathbf{KP}\prime}\mathbf{z_j} + \boldsymbol{\gamma}^{\mathbf{KP}\prime}\mathbf{t}\right)\right) \\
p_{20,jt}^{KP} &= \Phi\left(\mu_{20}^{KP} - \left(\boldsymbol{\varphi}^{\mathbf{KP}\prime}\mathbf{z_j} + \boldsymbol{\gamma}^{\mathbf{KP}\prime}\mathbf{t}\right)\right) - \Phi\left(\mu_0^{KP} - \left(\boldsymbol{\varphi}^{\mathbf{KP}\prime}\mathbf{z_j} + \boldsymbol{\gamma}^{\mathbf{KP}\prime}\mathbf{t}\right)\right) \\
&\vdots \\
p_{130,jt}^{KP} &= 1 - \Phi\left(\mu_{100}^{KP} - \left(\boldsymbol{\varphi}^{\mathbf{KP}\prime}\mathbf{z_j} + \boldsymbol{\gamma}^{\mathbf{KP}\prime}\mathbf{t}\right)\right)
\end{aligned}
$$

where $\boldsymbol{\gamma}^{\mathbf{KP}}$ is a vector of estimable parameters on the seed dummies in vector **t**, and μ_i^{KP} is the estimated break for payout *i*. Using these estimated probabilities with known and pooled seeds, we estimate another coefficient of risk aversion for each farmer, which we denote b_j^{KP}. Note that since estimated probabilities in this case are derived from a pooled model the expected utility relationship in Eq 3 must be slightly modified. Instead of estimating a farmer-specific coefficient of risk aversion that is different for each seed *t*, we now must pool all the estimated probabilities, outcomes and WTP observations for each farmer as follows:

Eq 6

$$1 = \sum_{i=1}^{9} p_{ijt}^{KP}\left[1 + \left(-WTP_{jt} + x_{it}\right) - b_j^{KP}\left(-WTP_{jt} + x_{it}\right)^2\right]$$

where again payouts i are in ascending order such that i={1=-30, 2=0, 3=20, …, 9=130}.While this estimated coefficient is seed-specific, we focus exclusively on each farmer's *average* coefficient of risk aversion over the six seeds since the probabilities are predicted from a probit model that pools all the seeds together. We denote this average coefficient as $\overline{b}_j^{KP}$.

<u>*EP3: Unknown & Pooled Seeds (UP)*</u>. For the final approach, assume we can no longer distinguish between seeds – i.e., we cannot see subscript t on *WTP* – and so can only estimate probabilities by pooling all the observed payouts together. At some level nearly all approaches pool various inputs, seed types, or other production methods. For example, Saha, Shumway and Talpaz (1994) pool all inputs into three variables, materials, capital and land. In this case, much of the variation in profit distributions may not be discernable from the data. In contrast to the *Known & Pooled* Approach, we can no longer control for seeds with seed dummies, and the predicted probabilities, p_{ij}^{UP} , are no longer seed-specific as follows

Eq 7

$$\begin{aligned}
x_{jt} &= \boldsymbol{\varphi}^{\mathbf{UP}\prime}\mathbf{z_j} + \varepsilon^{UP} \\
p_{-30,j}^{UP} &= \Phi\left(-\left(\boldsymbol{\varphi}^{\mathbf{UP}\prime}\mathbf{z_j}\right)\right) \\
p_{0,j}^{UP} &= \Phi\left(\mu_0^{UP} - \left(\boldsymbol{\varphi}^{\mathbf{UP}\prime}\mathbf{z_j}\right)\right) - \Phi\left(-\left(\boldsymbol{\varphi}^{\mathbf{UP}\prime}\mathbf{z_j}\right)\right) \\
p_{20,j}^{UP} &= \Phi\left(\mu_{20}^{UP} - \left(\boldsymbol{\varphi}^{\mathbf{UP}\prime}\mathbf{z_j}\right)\right) - \Phi\left(\mu_0^{UP} - \left(\boldsymbol{\varphi}^{\mathbf{UP}\prime}\mathbf{z_j}\right)\right) \\
&\vdots \\
p_{130,j}^{UP} &= 1 - \Phi\left(\mu_{100}^{UP} - \left(\boldsymbol{\varphi}^{\mathbf{UP}\prime}\mathbf{z_j}\right)\right)
\end{aligned}$$

Using these predicted probabilities with unknown and pooled seeds, we estimate a final coefficient of risk aversion for each farmer. Again, because the estimated probabilities are based on a pooled model, we estimate a single overall coefficient of risk aversion for each farmer, which we denote as b_j^{UP} .

B. Farmer Traits and Coefficients of Risk Aversion

With four different sets of estimated coefficients of risk aversion – three sets based on estimated probabilities and one comparable set based on true probabilities – we can now test for correlations between wealth and risk aversion by estimating the relationship between these coefficients of risk aversion and individual traits. We begin with an individual trait model that uses the average true coefficient of risk aversion, $\bar{\beta}_j$, as the dependent variable to establish the true correlation between wealth and risk aversion implied by our experimental data. Using these results as a benchmark, we assess whether estimated probabilities introduce spurious correlation between traits and risk preferences by comparing them to results for trait models with $\bar{b}_j^{KS}$, b_j^{KP} and b_j^{UP} as dependent variables. Lastly, we compare results for trait models with seed-specific coefficients β_{jt} and b_{jt}^{KS} as dependent variables.

With $\bar{\beta}_j$ as dependent variable, we estimate the following trait model:

Eq 8
$$\begin{aligned}\bar{\beta}_j &= \alpha_1 + \alpha_2 Age_j + \alpha_3 Edu_j + \alpha_4 TLU_j + \alpha_5 IrrLand_j + \alpha_6 Bt_j + \alpha_7 Wealth_j \\ &\quad + \boldsymbol{\varphi}_{\mathbf{v}}{}'\mathbf{v}_{\mathbf{j}} + \boldsymbol{\varphi}_{\mathbf{g}}{}'\mathbf{g}_{\mathbf{j}} + \varepsilon_j\end{aligned}$$

where *TLU* is herd size measured in tropical livestock units, *IrrLand* is the percent irrigated of total land holdings, and *Bt* is a dummy that indicates whether individual *j* has adopted Bt cotton. Fixed-effects are introduced into this model through a vector of village dummies **v** and a vector of order dummies **g** that indicate the order in which individual *j* was offered the experimental distributions.[6] *Wealth* is a factor analytic wealth index, which is described and discussed in the

[6] Recall that distribution B was always the first and last one (B1 and B2, respectively) offered to participants. This vector of dummies indicates the order in which distributions T, S, H, and L were presented to individual *j*.

Appendix. We replicate the trait model specified in Eq 8 for dependent variables $\overline{b}_j^{KS}$, b_j^{KP} and b_j^{UP}, as well as for the seed-specific dependent variables β_{jt} and b_{jt}^{KS}.

4 RESULTS

In this section, we present and discuss estimation results – first, from the ordered probit model used to estimate probabilities and, second, from the farmer trait models used to estimate the correlation between wealth and risk aversion.

Estimation results for the ordered probit models *EP1*, *EP2*, and *EP3* outlined above are shown in Table 3. Since the probabilities in the experiment are independent of individual traits, the statistical insignificance of the trait coefficients is not surprising. As shown in Figures 3 and 4,[7] however, these probability models do a decent job predicting the probabilities attached to specific outcomes in the experiment. In addition to these estimated probabilities, which are estimated based on the full trait vector shown in Table 3, we estimate two alternative sets of probabilities; the first excludes wealth from this trait vector, and the second uses a random variable in place of this trait vector.[8] As already mentioned, we use these alternative sets of estimated probabilities to identify how wealth and other traits in the probability model introduce spurious correlation between risk preferences and traits in subsequent estimations.

Using these estimated probabilities, we solve Eq 3 for the estimated coefficients of risk aversion discussed above. Histograms of $\overline{b}_j^{KS}$, b_j^{KP} and b_j^{UP} are superimposed on a histogram of the average true coefficient $\overline{\beta}_j$ in Figure 3. Since moving from $\overline{b}_j^{KS}$ to b_j^{KP} to b_j^{UP} entails greater restrictions – and, hence, less information – in the estimated probabilities model, it is not surprising that the distribution of average estimated coefficients becomes tighter and more

[7] Note that the average true probabilities depicted in Figure 4 are computed as $\left(\sum_{t=1}^{6} p_{it}\right)\Big/6$.

[8] Results from these alternative order probit models are available upon request.

symmetric over these progressively more restricted models. Also apparent in Figure 3 is the consistent downward shift in the distribution of risk aversion coefficients when estimated probabilities are used in lieu of true probabilities. The aggregate differences between true and estimated coefficients, both for average and seed-specific coefficients, are further confirmed in Table 3, which displays descriptive statistics for these coefficients and t statistics for the test that the means for true and estimated coefficients are equal.[9] It is important to note that this disparity between true and estimated coefficients of risk aversion is likely exaggerated in this case because the probabilities used in the experiment are clearly independent from individual traits. In field data, probabilities may indeed depend on traits, but because it is difficult to know how well estimated probabilities proxy for the probabilities perceived by individuals it is also difficult to judge how well estimated coefficients reflect true coefficients.

Table 4 displays estimation results from the trait model in Eq 8 with average coefficients of risk aversion as dependent variables. Comparing the standard errors and overall fit across these models, it is clear that using estimated probabilities introduce correlations between traits and these coefficients. When true probabilities are used, none of the trait coefficients are statistically significant, indicating that farmers' risk preferences are not measurably influenced by farmer characteristics. As we progressively presume to know less and less about these probabilities (i.e., as we move from *EP1* to *EP2* to *EP3*), statistical significance uniformly increases. Moreover, these patterns are robust when standard errors are bootstrapped.

To facilitate comparisons across these estimation results, we use graphical depictions of 90% confidence interval estimates of these trait coefficients. Figure 6 shows these interval estimates for the average true and average estimated coefficients of risk aversion. Spurious correlations introduced by estimated probabilities are evident in the tightening of the confidence

[9] Table 3 excludes 13 farmers who expressed some confusion during the experiment such that N=277.

intervals for *IrrLand* and *Wealth*. Since the relationship between wealth and risk aversion is often central to empirical risk research, we focus on the coefficient on *Wealth*. Figure 7 displays interval estimates for this coefficient in the b_j^{KP} and b_j^{UP} models for the different probability model specifications. Under the most restrictive approach (*EP3*), the source of spurious correlation between wealth and risk aversion is clear.

Next, we focus on seed-specific trait models that compare b_{jt}^{KS} and β_{jt} for $t=\{\mathrm{B1,B2,T,S,H,L}\}$. Instead of presenting the full set of regression results for these 12 models, we focus exclusively on interval estimates of the wealth coefficient. Figure 8 shows these interval estimates for all six distribution types and for the average over these distributions (i.e., $\overline{\beta}_j$ and $\overline{b}_j^{KS}$). There are two results worth noting in this figure. First, the estimated wealth coefficients for the true coefficient of risk aversion may be seed-specific, implying that the relationship between wealth and risk aversion may depend on qualitative features of payoff distributions. Second, the spurious correlation introduced into this relationship by estimated probabilities is due to the inclusion of wealth correlates in the estimation of probabilities and vanishes as these correlates are excluded from the estimation of probabilities.

5 CONCLUSION

Ever since risk aversion was formulated as an analytic concept, the correlation between wealth and measures of risk aversion has been central to empirical risk research. This paper highlights a common problem in this research that may complicate establishing this correlation. In empirical settings outside the economic laboratory, the probabilities that individuals face when making decisions (or their perceptions of these probabilities) are not observable and must be estimated, often via a production or profit function that is jointly estimated with a utility function. When these probabilities are estimated as a function of individual wealth or correlates of wealth, subsequent estimation of the correlation between wealth and risk preferences is potentially misleading. We use data from a field experiment in which probabilities are known to demonstrate how estimating probabilities can introduce spurious correlation.

APPENDIX

The Wealth Index & Risk Exposure

We computed the wealth index used in the trait models as Eq 8the product of a vector of farmer variables and a vector of corresponding factor analytic weights. We also computed a risk exposure index using a similar approach. We follow an iterative approach for selecting the variables included in the vectors for these wealth and risk exposure indices. Beginning with a broad set of variables, we estimate an initial weight vector and compute a residual correlation matrix. When off-diagonal residual correlation is greater than 0.10 between two variables, we retain the variable that seems to be more relevant or more reliable and remove the other, then re-estimate the weight vector using this more focused variable vector. (See Lawley and Maxwell (1971) for details about factor analysis and Sahn et al. (1999) and Lybbert et al. (2002) for applications of factor analysis that involve asset and wealth indices similar to those constructed in this section.)

The results of the estimation of these weights are shown in Table A1. The left panel of Figure A1 displays kernel density plots of the wealth and risk exposure indices.[10] The right panel of Figure A1 displays a scatter plot of the two indices with a kernel density regression line of the wealth index on the risk exposure index.[11] Despite the conventional wisdom that wealth directly shapes risk tolerance as revealed by asset allocation and production decisions, these two indices are clearly uncorrelated (correlation coefficient -0.06).

[10] Epanechnikov kernel with bandwidths of 0.18 and 0.17, respectively.
[11] Logistic kernel with bandwidth of 0.13.

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Figure 1 Map of surveyed villages in Salem and Perambalur districts of Tamil Nadu (TN), India (India map courtesy of www.theodora.com/maps, used with permission).

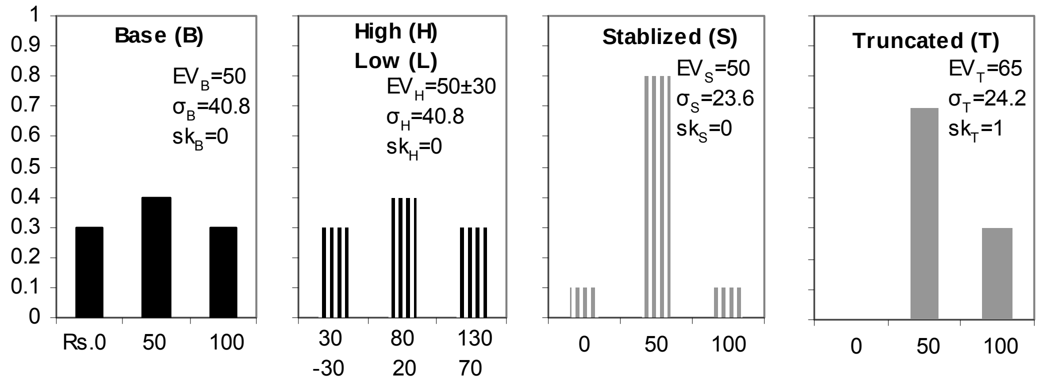


Figure 2 Marginal probability distributions for distribution types in experiment

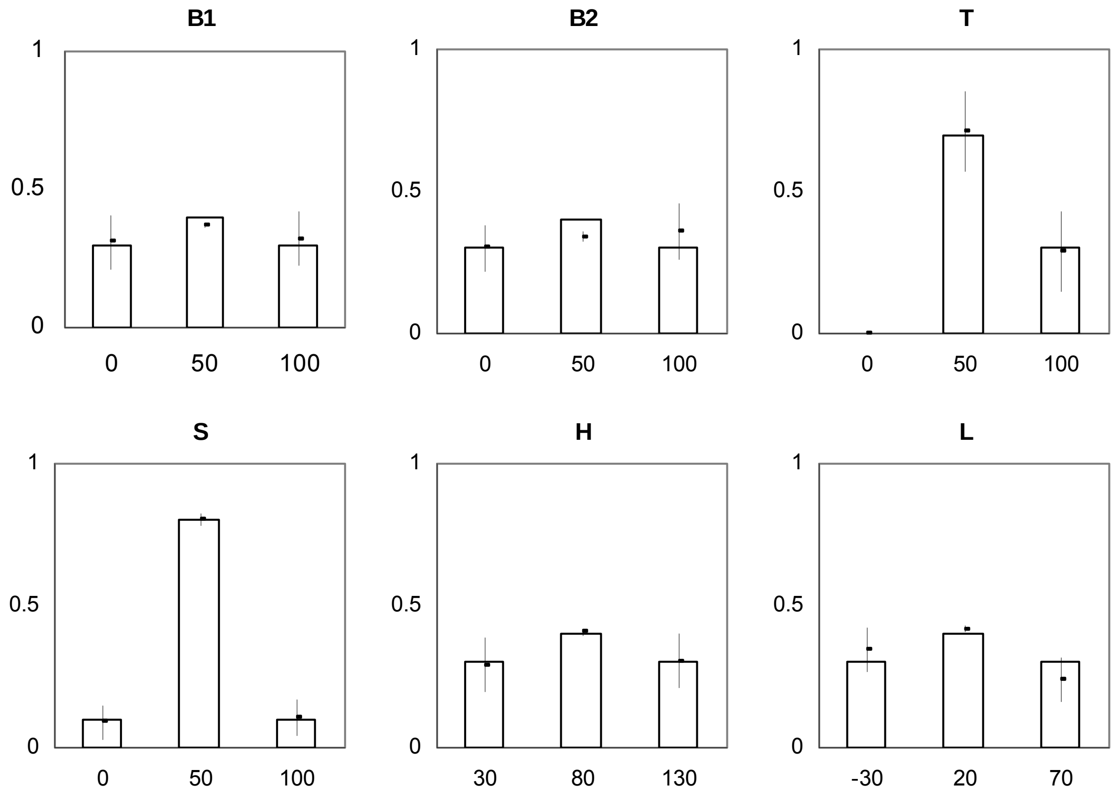


Figure 3 True probabilities (bars) and average p_{ijt}^{KS} (dash) ± 2 standard deviations (line).

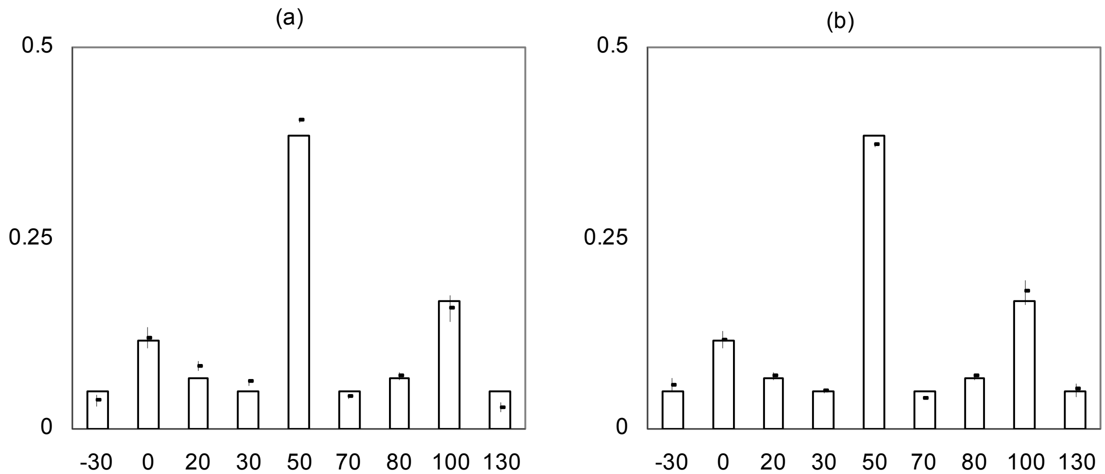


Figure 4 Average true probabilities (bars) and average (dots) ± 2 standard deviations (lines) for (a) p_{ijt}^{KP} and (b) p_{ij}^{UP}.

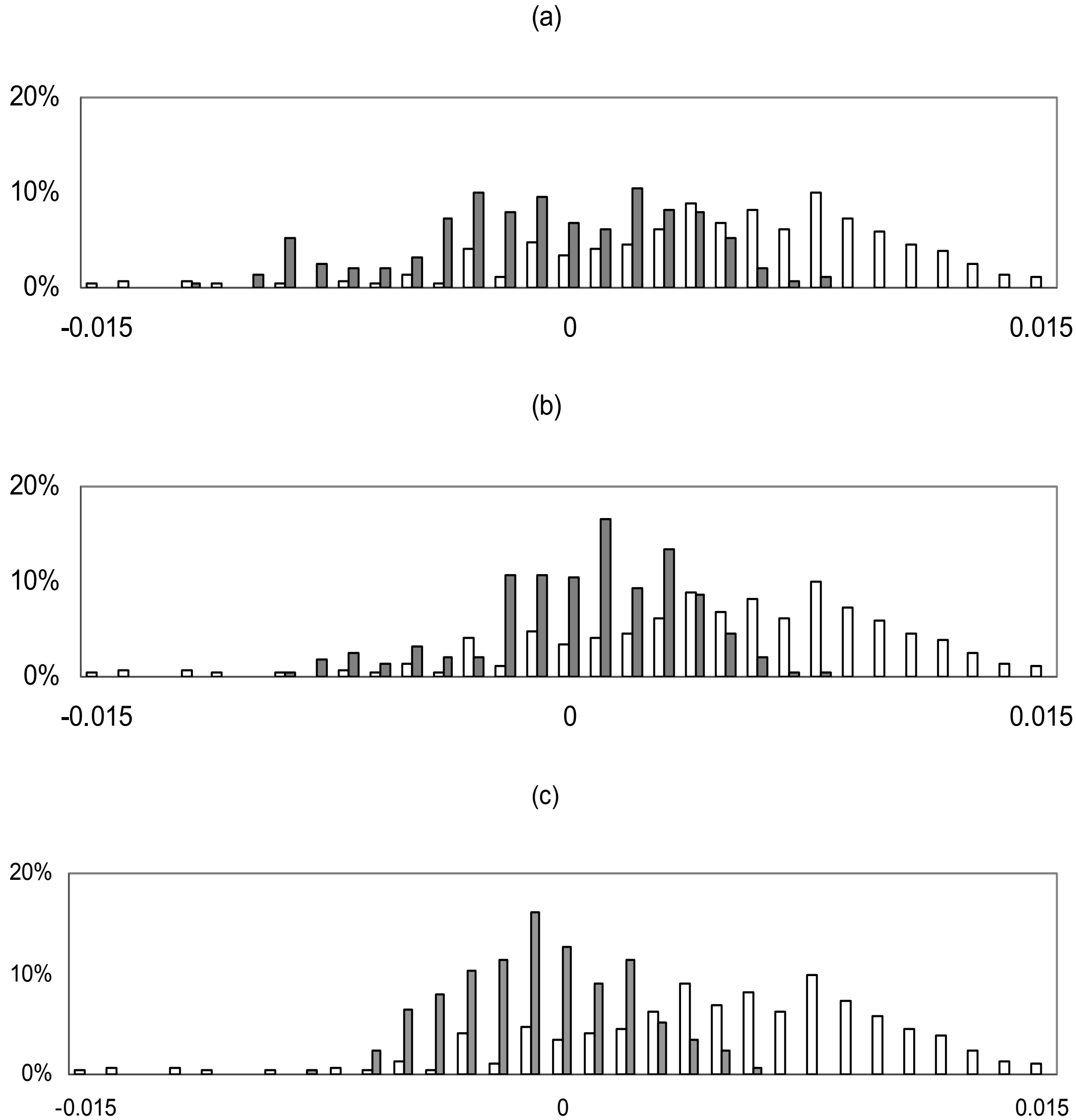


Figure 5 Histograms of average true risk aversion coefficient $\overline{\beta}_j$ (white) and average estimated coefficients (grey): (a) $\overline{b}_j^{KS}$ (b) b_j^{KP} and (c) b_j^{UP}.

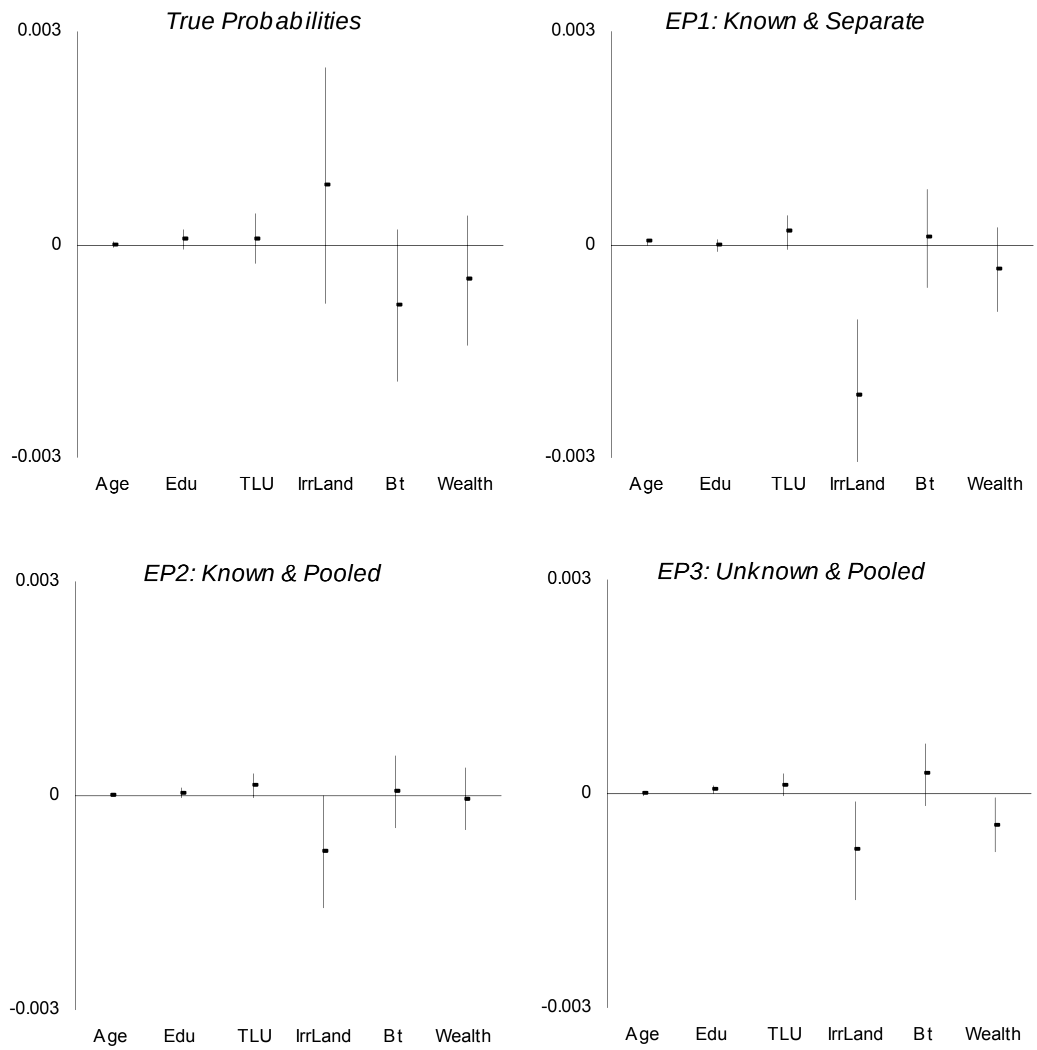


Figure 6 90% confidence interval estimates of trait model coefficients with average coefficient of risk aversion as dependent variables.

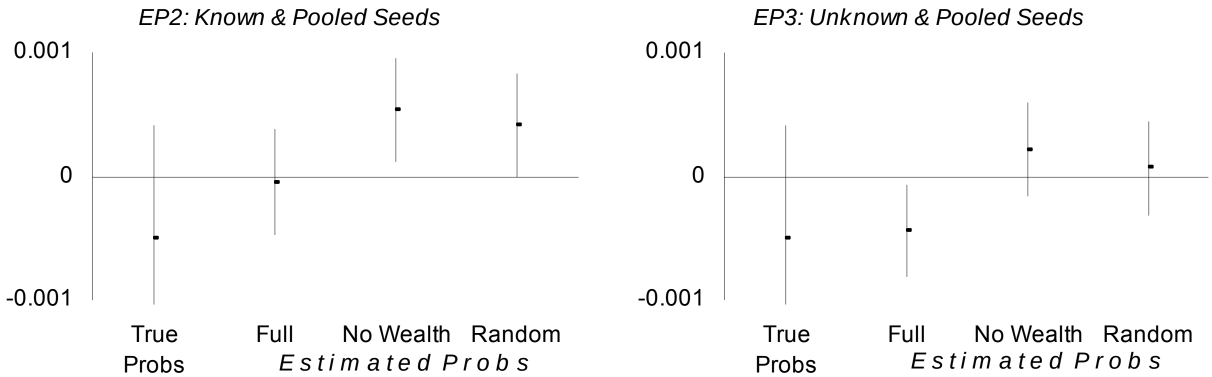


Figure 7 90% confidence interval estimates of wealth coefficient for average estimated betas with different explanatory variables in probability model

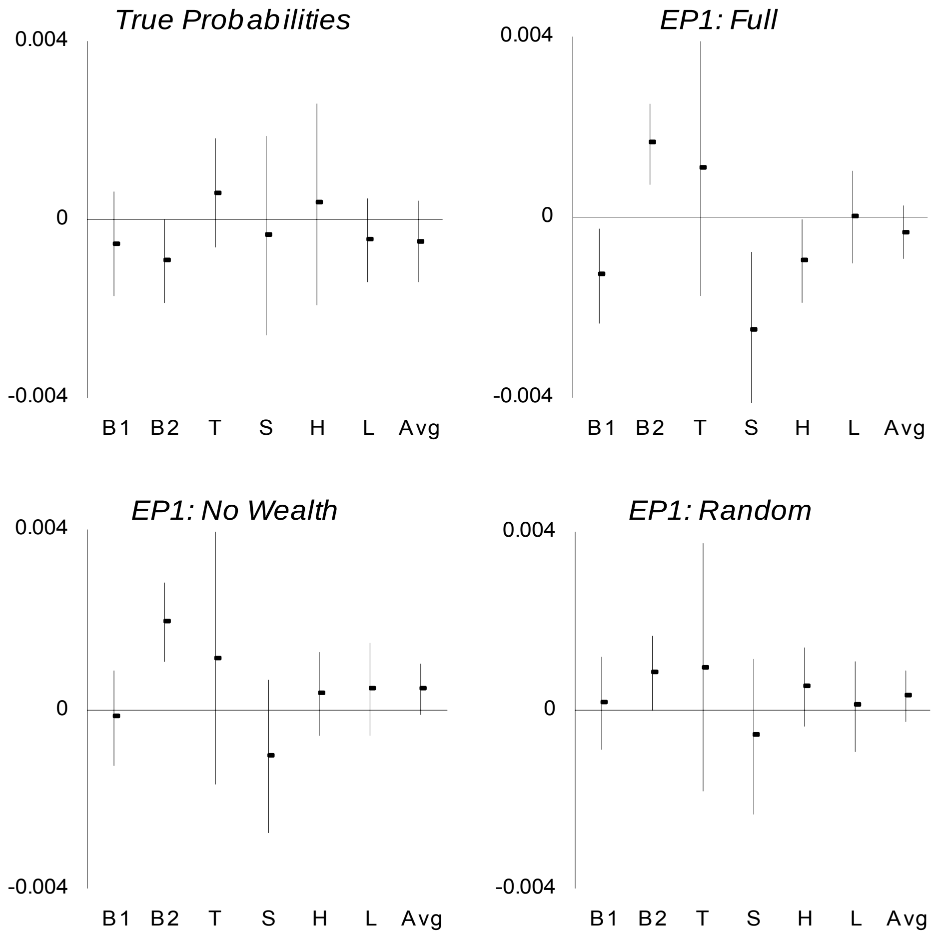
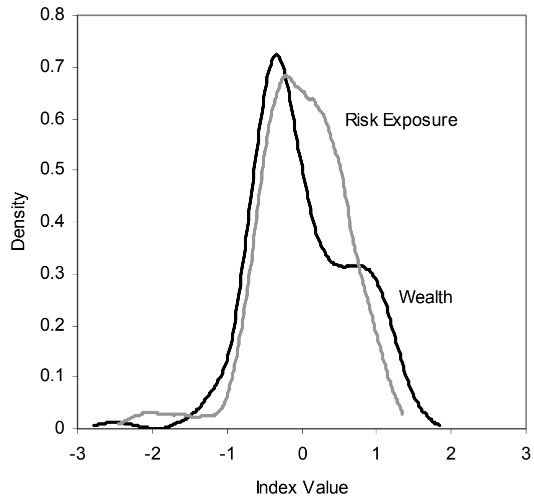


Figure 8 90% confidence interval estimates of wealth coefficient for seed-specific coefficients of risk aversion with different explanatory variables in probability model



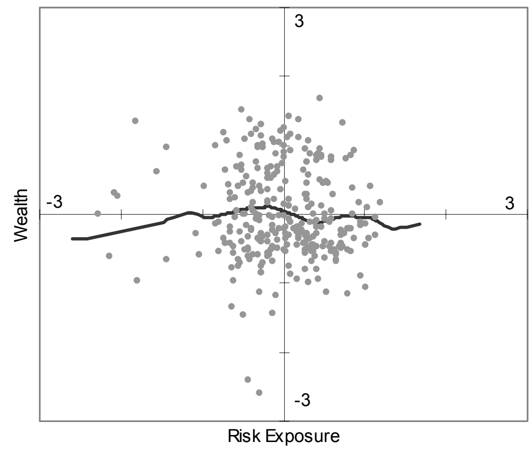


Figure A1 Non-parametric regressions of wealth index and risk exposure index densities (left) and scatter plot of wealth and risk exposure indices (right).

Table 1 Descriptive statistics for relevant variables

	Median	Mean	Std.Dev	Max	Min	# Min
Household Demographics, Wealth & Assets						
HH size	4	4.24	1.17	7	2	
Female {0,1}		0.01			0	287
Age	45	43.64	11.39	77	19	
Education (yrs)	5	4.82	4.52	20	0	105
House w/ concrete floor {0,1}		0.87				
Tractor {0,1}		0.04				
Television {0,1}		0.33				
Telephone {0,1}		0.09				
Radio {0,1}		0.73				
Total annual expenses (Rs)†	6,500	11,490	14,416	118,000	0	2
Tropical livestock units	2	1.80	1.66	10	0	66
Land (acres)	5	6.67	5.60	50	0	1
% irrigated land	25%	33%	36%	100%	0	115
% in cotton	24%	28%	29%	100%	0	88
% in maize	50%	46%	33%	100%	0	65
% in chilies	0%	2%	6%	67%	0	254
% in paddy	0%	8%	14%	100%	0	184
Farm Management Goals (rank)						
Increase yield	1	1.3	0.7			
Stabilize yield	4	4.1	1.3			
Protect against crop loses	3	2.7	1.1			
Lower production costs	3	3.6	1.4			
Increase harvest quality	4	4.2	1.2			
Efficiently use water	6	5.0	1.5			
Risk Exposure of Productive Income						
% income from 'very risky' sources	40	36	33	100	0	109
% ... from 'no risk' sources	0	6	18	100	0	244
% ... exposed to high weather risk	40	39	35	100	0	104
% …exposed to high market risk	30	35	37	100	0	129
% …exposed to high pest risk	40	37	31	100	0	89
High-Stakes WTP in Experiment						
Average [Base (B)]‡	44	45	12	85	14.5	
High (H)	60	58	17	99	20	
Stabilized (S)	45	44	13	95	10	
Truncated (T)	50	51	15	99	10	
Total earnings from experiment (Rs)	63	64	11	135	44	

† Includes expenses on clothes, education, medicine/health, and electronics.

‡ The average of the two high-stakes seasons for B.

Table 2 Ordered probit results for predicting probabilities (standard errors in parentheses)

	EP1: Known & Separate Seeds						*Pooled Seeds*	
t =	B1	B2	T	S	H	L	*EP2: Known*	*EP3: Unknown*
Age	-0.011	0.002	-0.004	0.009	0.002	0.0002	-0.0007	-0.0007
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.002)	(0.002)
Edu	-0.009	-0.011	0.043	0.017	-0.023	0.0001	-0.003	-0.002
	(0.016)	(0.016)	(0.019)	(0.019)	(0.016)	(0.016)	(0.006)	(0.006)
Wealth	-0.088	-0.023	-0.105	-0.097	-0.088	-0.051	-0.059	-0.050
	(0.117)	(0.116)	(0.139)	(0.133)	(0.115)	(0.116)	(0.044)	(0.044)
Irr.Land	0.008	0.011	-0.002	-0.044	0.022	0.038	0.010	0.008
	(0.023)	(0.024)	(0.028)	(0.027)	(0.023)	(0.024)	(0.009)	(0.009)
Non-Irr.Land	-0.002	0.028	-0.004	0.023	-0.003	0.005	0.006	0.005
	(0.018)	(0.019)	(0.021)	(0.021)	(0.018)	(0.019)	(0.007)	(0.007)
B2 {0,1}							0.068	
							(0.086)	
T {0,1}							0.406	
							(0.087)	
S {0,1}							0.021	
							(0.087)	
H {0,1}							0.877	
							(0.087)	
L {0,1}							-1.040	
							(0.088)	
Log Likelihood	-316	-316	-170	-180	-313	-310	-3034	-3276
N =	290	290	290	290	290	290	1740	1740

Table 3 Descriptive statistics for true and estimated risk aversion coefficients.

	Mean	Std.Dev.	Min	Max	t statistic*	Corr.
$\bar{\beta}_j$	0.0046	0.0053	-0.0145	0.0146		
$\bar{b}^{KS}_j$	-0.0011	0.0041	-0.0122	0.0080	-10.10	0.03
b^{KP}_j	0.0001	0.0030	-0.0093	0.0073	-9.01	0.04
b^{UP}_j	-0.0012	0.0027	-0.0089	0.0056	-12.03	-0.06
$\beta_{j,B1}$	0.0032	0.0070	-0.0128	0.0129		
$b^{KS}_{j,B1}$	-0.0023	0.0071	-0.0129	0.0129	-6.52	0.05
$\beta_{j,B2}$	0.0088	0.0057	-0.0129	0.0129		
$b^{KS}_{j,B2}$	0.0024	0.0058	-0.0124	0.0151	-9.28	0.04
$\beta_{j,T}$	0.0156	0.0112	-0.0217	0.0218		
$b^{KS}_{j,T}$	0.0055	0.0171	-0.0249	0.0248	-5.91	0.12
$\beta_{j,S}$	0.00002	0.0151	-0.0223	0.0224		
$b^{KS}_{j,S}$	-0.0039	0.0125	-0.0230	0.0229	-2.38	0.08
$\beta_{j,H}$	0.0032	0.0062	-0.0129	0.0129		
$b^{KS}_{j,H}$	-0.0024	0.0063	-0.0131	0.0131	-7.52	-0.03
$\beta_{j,L}$	-0.0036	0.0077	-0.0129	0.0125		
$b^{KS}_{j,L}$	-0.0061	0.0062	-0.0133	0.0134	-3.03	-0.01

* Tests the null that an estimated b is equal to the corresponding true β.

Table 4 Estimation results from trait model with average coefficient of risk aversion (x 100,000) as dependent variable (standard errors in parentheses)

	True Probabilites	*EP1: Known & Separate*	*EP2: Known & Pooled*	*EP3: Unknown & Pooled*
Age	-0.09	3.02	1.13	0.63
	(2.98)	(1.92)	(1.40)	(1.24)
Edu	7.00	-1.50	3.66	5.12
	(7.97)	(5.14)	(3.74)	(3.31)
TLU	8.26	17.41	12.80	12.23
	(21.76)	(14.03)	(10.22)	(9.04)
IrrLand	82.26	-211.62 *	-78.85 *	-79.51 *
	(100.49)	(64.80)	(47.20)	(41.72)
Bt {0,1}	-85.25	9.33	5.72	26.76
	(64.63)	(41.68)	(30.36)	(26.83)
Wealth	-50.34	-34.31	-4.80	-44.09 *
	(55.18)	(35.58)	(25.92)	(22.91)
Constant	422.29 *	-204.65 *	-60.41	-181.68 *
	(158.38)	(102.13)	(74.39)	(65.75)
R-Sqr	0.07	0.37	0.38	0.40
N=	277	277	277	277

Table A1 Factor analysis results for wealth and risk exposure indices

Variable	Std. Coeff.	Mean	Std.Dev.	Hypothesis Tests: Hypotheses	df	ChiSq	Pr>ChiSq
========== Wealth Index † ==========							
Ln(Non-Irr.Land)	0.33	1.4	0.79	H_0: No common factors	10	40.7	< 0.0001
Ln(TLU)	0.19	0.84	0.60	H_A: At least one factor			
Television {0,1}	0.53	0.33	0.47	H_0: One factor is sufficient	5	3.6	0.61
Concrete floor {0,1}	0.23	0.87	0.34	H_A: More factors needed			
Ln(Selected Expenses*)	0.42	8.8	1.2				
========== Risk Exposure Index ‡ ==========							
% Crop Lost**	-0.12	63	20	H_0: No common factors	6	17.9	0.006
% Income from 'Very Risky' source	0.40	35	33	H_A: At least one factor			
% Income from 'No Risk' source	-0.31	6.2	18	H_0: One factor is sufficient	2	2.8	0.23
Ln(Irr.Land)	-0.10	0.85	0.80	H_A: More factors needed			

† Motorcycle {0,1} and Radio {0,1} (Tractor {0,1}) were removed after iteration one (two) to reduce multicollinearity.

‡ Log TLU (% Income in 'worst' season) were removed after iteration one (two) to reduce multicollinearity.

* Total household expenses on clothing, education, electronics, and medicine.

** Measured as crop lost in the 'worst season in past five years' as percent of average harvest.