Economists frequently focus on correlations between wealth and risk preferences but rarely observe the probabilities needed to test this relationship empirically. These unobserved probabilities are typically estimated via profit or production functions conditioned on wealth correlates, which may leave statistical fingerprints on subsequently-estimated risk aversion coefficients and confound correlations between wealth and risk preferences. Using data from an experiment with observable probabilities, we compare risk aversion coefficients based on true probabilities with those based on probabilities estimated using standard approaches and show how estimated probabilities can change risk aversion coefficients substantially and introduce spurious correlation between risk aversion and wealth.

**Key words**: decreasing absolute risk aversion, expected utility, experimental economics, risk aversion, wealth.
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 Arrow’s hypotheses relating risk to wealth.

In this article, 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.

**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 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 payoff level. As with several subsequent and similar studies (see Binswanger and Sillers 1983), Binswanger finds no statistically significant evidence that partial risk aversion is correlated with wealth or other traits and concludes that, “differences in investment behavior observed among farmers facing similar technologies and risks cannot be explained primarily by differences in their [risk] attitudes but would have to be explained by differences in their constraint sets, such as access to credit, marketing, extension, etc.” (p. 406). Others have highlighted a similar pitfall of confounding risk aversion and constraints such as credit market imperfections (e.g., Eswaran and Kotwal 1990; Masson 1972). Binswanger (1982) generalized these concerns with the observation that researchers normally observe very little about the nature and distribution of the risks they study empirically. In this same spirit, we argue that the critical distinction between risk preferences and constraint sets as the source of behavioral differences is muddled whenever probabilities are unobserved and estimated using correlates of an individual’s constraint set such as farm size, technology, wealth, or other personal traits. Using an experimental approach with known probabilities we demonstrate explicitly how confusion between constraint sets and risk preferences can introduce misleading correlations between risk aversion and wealth.

Others have used econometric estimation using data on investment or production decisions in order to relate wealth or socio-economic data to risk aversion. Saha, Shumway, and Talpaz (1994) provide a summary of many of these studies related primarily to agricultural production. Such econometric studies use either structural estimation based on a parametric utility model or reduced form

1 In contrast, we use willingness to pay data to obtain more detailed information on risk aversion parameters than is possible using this type of dichotomous experimental design.
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, Just, and Zilberman 1997; Chavas and Holt 1990; Pope and Just 1991). Two primary drawbacks, noted by Holt and Chavas (2001), 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. Econometric estimation will often 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). Thus common estimation techniques that allow for heterogeneous risk aversion parameters across socio-economic variables, but not heterogeneous risk perception (e.g., Bar-Shira, Just, and Zilberman 1997; Cicchetti and Dubin 1994; and virtually all studies examining wealth and risk aversion) may misinterpret the underlying behavior.

Holt and Chavas (2001) suggest that structural estimation is underutilized in measuring properties of risk aversion. Antle (1987), Chavas and Holt (1996), and Saha, Shumway, and Talpaz (1994) each use a structural approach to measure risk parameters. Originally, employing a structural approach to test Arrow’s hypotheses was difficult because no functional form had been proposed that could satisfy the hypotheses. Saha’s expo-power utility function (employed in Saha, Shumway, and Talpaz) 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 may often fundamentally contradict the data that produced them. Using the conditional profit distribution estimated by Saha, Shumway, and Talpaz, 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 acreage 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 to estimate a realistic conditional profit distribution—a prerequisite for using the structural approach in econometric estimation. This difficulty arises for several reasons including: limited availability of suitably disaggregated panel data, a practical need for production functions to include a simpliﬁed set of inputs (often just capital, labor and materials) that will necessarily ignore the impact of individual inputs on risk, the difficulty involved in discerning and modeling the timing of decisions and the realization of uncertainty throughout the growing season. We overcome the inherent problems of estimation encountered in econometric studies of risk aversion by employing experiments. By using hypothetical seed distributions, we can observe the exact distribution of profits available to decision-makers, including the underlying probabilities.

Data

This article 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). 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 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, Hovis and Schulze 1999), and the well-known Becker–DeGroot–Marschak (BDM) mechanism (Becker, DeGroot and Marschak 1964). As shown in figure 2, there were five payoff distributions in the experiment: a benchmark base distribution (B), a high distribution with a higher mean payoff (H), a low distribution with a lower mean payoff (L), a stabilized distribution with lower variance (S), and a truncated distribution with positive skewness (T). Figure 2 shows the marginal probability distributions and the expected value (EV), standard deviation (σ), and skewness (sk) for each of
these distributions.\textsuperscript{2} Every farmer valued each of these payoff distributions several times, first during practice rounds then in a final high stakes round.

To control for learning and ordering effects, all farmers started and ended with the benchmark distribution \(B\) (denoted \(B_1\) and \(B_2\), respectively), between which distributions \(H\), \(L\), \(S\), and \(T\) were randomly ordered (see Lybbert [2004] for more details about the experiment). These data have been used elsewhere to assess poor farmers’ valuation of pro-poor seeds and to explore the strengths and weaknesses of field experiments as a methodology in conducting policy-relevant research (Lybbert 2006).

Estimation

In this section, we describe two sets of estimation procedures. The first set uses farmers’ willingness to pay (WTP) for experimental payoff 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 subsections A and B, respectively.

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 payoff distribution probabilities. In particular, the true probabilities approach assumes we know the true underlying probabilities farmers faced when stating 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 \textit{ex post} payoff amounts. These three EP approaches become progressively more restrictive. They differ according to whether we can distinguish between the different seeds offered to farmers—i.e., whether we know which of the nine possible experimental payoffs, is, were relevant \textit{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 and thereby offers the greatest flexibility. The more restrictive approach EP2 estimates probabilities by pooling all the \textit{ex post} payoff amounts and adding a dummy variable for each seed in this pooled equation. The yet more restrictive approach EP3 assumes we cannot distinguish between seeds and 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. The results from each of these methods 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 straightforward approach, we solve for the risk preferences implied by farmer \(j\)’s WTP for seed \(t\) using the expected utility relationship

\begin{equation}
U\left(w_j \mid \beta_{jt}\right) = \sum_i \pi_{jt} U\left(w_j - \text{WTP}_{jt} + x_{jt} \mid \beta_{jt}\right)
\end{equation}

where \(U\) is the utility of wealth function, \(w_j\) represents wealth of individual \(j\), \(\beta_{jt}\) is a risk aversion parameter for individual \(j\) and payoff distribution \(t\), \(\pi_{jt}\) is the probability of outcome \(i\) in payoff distribution \(t\), and \(x_{jt}\) is payoff for outcome \(i\) in distribution \(t\). The experiment described above provides data for variables \(\pi_{jt}\), WTP\(_{jt}\), and \(x_{jt}\); the companion questionnaire provides data for \(w_j\). For any function \(U\), then, we can solve for the risk aversion parameter \(\beta_{jt}\) that rationalizes farmer \(j\)’s WTP\(_{jt}\). This parameter simply adjusts the curvature of \(U\) to maintain the expected utility equality in (1).

Each individual faced five different payoff 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 WTP data, such

\textsuperscript{2} 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.
estimators are biased even when distributions of the underlying uncertainty are known. Any amount of error in the relationship in (1) leads to not only biased, but inconsistent estimates. The size of this bias will depend on the magnitude of the error variance. To produce a consistent estimate of risk preferences, we solve for \( \beta_{jt} \) separately for each observation \( t \) of individual \( j \), then compute \( \hat{\beta}_j = \sum \beta_{jt} / T \).

We use the following quadratic utility function to solve for individual risk preferences,

\[
U(w) = 1 + (w_0 - w_1) - \beta (w_0 - w_1)^2
\]

where \( \beta \) is the local Arrow–Pratt measure of absolute risk aversion, \( w_0 \) is initial wealth and \( w_1 \) is end-of-period wealth. Because we are interested only in obtaining a local measure of risk aversion specific to each risky choice, the quadratic utility function is sufficiently flexible to meet our needs. Quadratic utility functions

\[
\min_{\beta} \sum_{t=1}^{T} \left[ \sum_{i=1}^{I} \pi_i(t) (e^{-\beta(w + x_{it} - WTP_t)}) - e^{-\beta w} \right]^2.
\]

This yields a first order condition:

\[
\sum_{t=1}^{T} \left[ \sum_{i=1}^{I} \pi_i(t) (e^{-\beta(w + x_{it} - WTP_t)}) - 1 \right] \times \left[ - \sum_{i=1}^{I} \pi_i(t) (w + x_{it} - WTP_t) (e^{-\beta(w + x_{it} - WTP_t)}) \right] = 0.
\]

However, if WTP is observed with error, represented by \( e_i \), this non-degenerate \( e_i \) will systematically alter the first order condition for estimation. In particular, the difference in first order conditions at the true \( \beta \) with and without error is given by

\[
E \left[ \frac{\delta \text{SSE}(e_i = 1)}{\delta w} - \frac{\delta \text{SSE}(e_i = 0)}{\delta w} \right] \beta^* = \sum_{i=1}^{I} \left[ \frac{(e^{\beta* w^2} - e^{\frac{1}{2} \beta^* w^2})}{\beta^*} \right] \times \left[ - \sum_{t=1}^{T} \sum_{i=1}^{I} \pi_i(t) (w + x_{it} - WTP_t) (e^{-\beta^*(w + x_{it} - WTP_t)}) \right] \times \left[ e^\beta \sigma^2 e^{\frac{1}{2} \beta^* w^2} \sum_{i=1}^{I} \sum_{t=1}^{T} (e^{\beta^*(w + x_{it} - WTP_t)}) \right]
\]

In general this will have a value of zero only when \( \sigma = 0 \), or when the distribution of the error is degenerate. Moreover, the derivative of this difference with respect to \( \sigma \) is negative, implying that increasing the variance of \( e \) will increase the estimate of \( \beta \). Additionally, increasing \( T \) will increase this bias. Similar problems occur with other well known functional forms.

\[^3\] This result obtains because willingness-to-pay (WTP) data generates an equality between utility statements rather than a first order condition. This equality creates an odd interaction with the exponential structure of typical utility functional forms. For example, we could try minimizing the sum of squared differences between expected utility and the current utility:

\[
sse = \sum_{t=1}^{T} \sum_{i=1}^{I} \pi_i(t) (e^{-\beta(w + x_{it} - WTP_t)}) - e^{-\beta w} \]

where payoffs \( x_{it} \) are sorted for each seed \( t \) in ascending order: \( i = \{1 = \text{Low}, 2 = \text{Mid}, 3 = \text{High}\} \).\(^4\) Note that \( \beta_{jt} \) 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 \( \beta_{jt} \) and the average over all six seeds for each individual, denoted by \( \hat{\beta}_j \), 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 (3), but assume we can no longer observe \( \pi_{it} \) and must estimate probabilities instead. With estimated probability \( \hat{\pi}_{jt} \)— which is specific to individual \( j \) if probabilities are conditioned by farmer traits such as education, land holdings, and wealth—this relationship produces an estimated probability coefficient of risk aversion, \( b_{jt} \), rather than the true probability coefficient \( \beta_{jt} \). Before delving into different ways of estimating \( \pi_{jt} \), 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, \( \pi_{jt} \) and \( x_{it} \)

\[^4\] 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 placeholder for the numeric value of the outcome.
are more problematic. In most field settings we observe bounds on WTP as implied by whether an individual adopts a technology or not at the going market prices. For example, Cicchetti and Dubin (1994) estimated risk aversion coefficients by observing whether individuals insured against telephone line trouble, the price of insurance, and the rate of line trouble. This binary choice information provides decidedly less information about the value of the gamble involved. Our knowledge of the profit distribution facing individuals—the field data analogue of the experimental payoff distribution—is often 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.

**EP1: Known & Separate Seeds (KS).** This approach offers the greatest flexibility in estimating the underlying technology. It assumes we know precisely which seed farmers faced when they formulated their WTP—i.e., we see subscript \( t \) on WTP—and can therefore estimate separate probability equations for each seed. This Known and Separate Seeds approach uses the observable ex post payoffs 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 payoff distributions, we use an ordered probit model to estimate \( p_{ijt}^{KS} \) for \( i = \{1 = L, 2 = M, 3 = H\} \) and \( t = \tau \) as follows

\[
\begin{align*}
\dot{x}_{j|t=\tau} &= \varphi_{\tau}^{KS}z_j + \epsilon^{KS} \\
p_{L,jt}^{KS} &= \Phi(-\varphi_{\tau}^{KS}z_j) \\
p_{M,jt}^{KS} &= \Phi(\mu_{Mt}^{KS} - \varphi_{\tau}^{KS}z_j) - \Phi(-\varphi_{\tau}^{KS}z_j) \\
p_{H,jt}^{KS} &= 1 - \Phi(\mu_{Mt}^{KS} - \varphi_{\tau}^{KS}z_j)
\end{align*}
\]

where \( x_{j|t=\tau} \) is the observed payoff for farmer \( j \) and seed \( \tau \), \( z_j \) is a column vector of traits for farmer \( j \) and \( \varphi_{\tau}^{KS} \) is a vector of estimable parameters for seed \( \tau \), \( \epsilon^{KS} \) is an error term, \( \mu_{Mt}^{KS} \) is the estimated break between \( i = L \) and \( i = M \), and \( \Phi \) 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 \( z_j \): age, education, a wealth index, 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 (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 estimated probability coefficient of risk aversion for each farmer using the expected utility relationship in (3), which we denote by \( b_{j\tau}^{KS} \). This coefficient is directly comparable to the true probability coefficient \( \beta_{j\tau} \) since both are seed- and individual-specific. We also compute and analyze an average coefficient for each farmer, denoted by \( \bar{b}_{j}^{KS} \).

**EP2: Known & Pooled Seeds (KP).** This slightly more restrictive 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 exist 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 payoffs—\( p_{ij}^{ KP} \) for \( i = \{-30, 0, 20, 30, 50, 70, 80, 100, 130\}\)—are predicted with a single estimated ordered probit model as follows

\[
x_{jt} = \phi^{KP} z_j + \gamma^{KP} t + \epsilon^{KP}
\]

\[
p_{-30,jt}^{ KP} = \Phi(- (\phi^{KP} z_j + \gamma^{KP} t))
\]

\[
p_{0,jt}^{ KP} = \Phi(\mu_0^{ KP} - (\phi^{KP} z_j + \gamma^{KP} t))
\]

\[
p_{30,jt}^{ KP} = \Phi(\mu_{30}^{ KP} - (\phi^{KP} z_j + \gamma^{KP} t))
\]

\[
p_{130,jt}^{ KP} = 1 - \Phi(\mu_{130}^{ KP} - (\phi^{KP} z_j + \gamma^{KP} t))
\]

(5)

where \( \gamma^{KP} \) is a vector of estimable parameters on the seed dummies in vector \( t \), and \( \mu_{ij}^{ KP} \) is the estimated break for payoff \( i \). Using these estimated probabilities with known and pooled seeds, we estimate another coefficient of risk aversion for each farmer, which we denote \( b_{ij}^{ KP} \). Note that since estimated probabilities in this case are derived from a pooled model, the expected utility relationship 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:

\[
1 = \sum_{i=1}^{9} p_{ij}^{ KP} [1 + (-\text{WTP}_{jt} + x_{it}) - b_{ij}^{ KP} (-\text{WTP}_{jt} + x_{it})^2]
\]

(6)

where again payoffs \( i \) are in ascending order such that \( i = \{-30, 20, 0, 30, 20, \ldots, 9 = 130\}\). 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 estimated probability coefficient by \( b_{j}^{ KP} \).

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 estimated probability coefficient of risk aversion for each farmer, which we denote by \( b_{j}^{ UP} \).

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 probability coefficient of risk aversion, \( \hat{\beta}_{j}^{T} \), 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 \( b_{j}^{ KS} \), \( b_{j}^{ KP} \), and \( b_{j}^{ UP} \) as dependent variables. Lastly, we compare results for trait models with seed-specific coefficients \( \beta_{j} \) and \( b_{j}^{ KS} \) as dependent variables.
With $\tilde{\beta}_j$ as dependent variable, we estimate the following trait model:

$$
\tilde{\beta}_j = \alpha_1 + \alpha_2 A_g + \alpha_3 Edu_j \\
+ \alpha_4 TLU_j + \alpha_5 IrrLand_j + \alpha_6 B_t_j \\
+ \alpha_7 Wealth_j + \psi_j v_j + \psi_j g_j + \epsilon_j
$$

(8)

where TLU$_j$ is herd size measured in tropical livestock units, IrrLand$_j$ is the percent irrigated of total land holdings, and B$_t_j$ 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 $v_j$ and a vector of order dummies $g_j$ that indicate the order in which individual $j$ was offered the experimental distributions. Wealth is a factor analytic wealth index. For descriptive statistics of these variables and a description of the construction of the wealth index, see Lybbert (2004, 2006). We replicate the trait model specified in (8) for dependent variables $\bar{\beta}^{KS}_j$, $\bar{b}^{KP}_j$, and $b^{UP}_j$, as well as for the seed-specific dependent variables $\beta_j$ and $b^{KS}_j$.

### Results

In this section, we present and discuss results from our outlined estimation approaches. We with results from the ordered probit model used to estimate probabilities, then move to results 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—in equations (4), (5), and (7), respectively—are shown in table 1. None of the coefficients on trait variables in these probit estimations are significant, which is expected since the probabilities in the experiment are entirely independent of individual traits. The coefficients on seed dummies in the EP2 model are significant for distributions with a different mean than B1 (the comparison distribution). The insigificance of the coefficients on the B2 and S dummies is not surprising since B2 is identical to B1 and S is very similar to B1 (see figure 2).
Predicted probabilities from model EP1 are shown in figure 3 with true probabilities displayed for comparison. Predicted probabilities from models EP2 and EP3 are similarly shown in figure 4. As depicted in these figures, these ordered probit models do a decent job predicting the probabilities of specific outcomes in the experiment. In addition to these estimated probabilities, which are estimated based on the full trait vector shown in table 1, we estimate two alternative sets of probabilities: the first excludes the wealth index from the trait vector and the second uses a random variable in place of this trait vector. 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 (3) for the estimated coefficients of risk aversion discussed above. Histograms of $\hat{b}_j^{KS}$, $\hat{b}_j^{KP}$, and $\hat{b}_j^{UP}$ are superimposed on a histogram

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Note that the average true probabilities depicted in Figure 4 are computed as $(\sum_{t=1}^6 p_{ij})/6$. 

---

Figure 3. True payoff probabilities (bars) and estimated probabilities for known and separate seeds $p_{ij}^{KS}$, and for six treatment distributions (average [dash] ± 2 standard deviations [line]; payoffs in rupees on x-axis)

Figure 4. Average true probabilities (bars) and estimated probabilities for (a) known and pooled seeds, $p_{ij}^{KP}$, and (b) unknown and pooled seeds, $p_{ij}^{UP}$ (average [dash] ± 2 standard deviations [line]; payoffs in rupees on x-axis)
Figure 5. Histograms of average true probabilities coefficient of risk aversion, $\bar{\beta}_j$ (white), and estimated probabilities coefficients (gray) for: (a) known and separate seeds, $\bar{b}^{KS}_j$, (b) known and pooled seeds, $b^{KP}_j$, and (c) unknown and pooled seeds, $b^{UP}_j$.

of the average true probabilities coefficient $\bar{\beta}_j$ in figure 5. Since moving from $\bar{b}^{KS}_j$ to $b^{KP}_j$ to $b^{UP}_j$ 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 symmetric over these progressively more restricted models. Also apparent in figure 5 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 2, which displays descriptive statistics for these coefficients and $t$ statistics for the test that the means for true and estimated coefficients are equal. It is important to note that this disparity between true and estimated coefficients of risk aversion is exaggerated in this case because the probabilities used in the experiment are clearly unrelated to 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 3 displays estimation results from the trait model in (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 farmer risk preferences are not

7 Table 3 excludes 13 farmers who expressed some confusion during the experiment such that $N = 277$. 
measurably influenced by farmer traits. As we progressively presume to know 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.

Table 2. Descriptive Statistics for Coefficients of (Local) Absolute Risk Aversion with True Probabilities (b) and Estimated Probabilities (b̂)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Min</th>
<th>Max</th>
<th>t statistic</th>
<th>Corr.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average Coefficients of Risk Aversion</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>β̂_{j}</td>
<td>0.0046</td>
<td>0.0053</td>
<td>-0.0145</td>
<td>0.0146</td>
<td></td>
<td></td>
</tr>
<tr>
<td>β̂_{KS}</td>
<td>-0.0011</td>
<td>0.0041</td>
<td>-0.0122</td>
<td>0.0080</td>
<td>-10.10</td>
<td>0.03</td>
</tr>
<tr>
<td>b_{j,KP}</td>
<td>0.0001</td>
<td>0.0030</td>
<td>-0.0093</td>
<td>0.0073</td>
<td>-9.01</td>
<td>0.04</td>
</tr>
<tr>
<td>b_{j,UP}</td>
<td>-0.0012</td>
<td>0.0027</td>
<td>-0.0089</td>
<td>0.0056</td>
<td>-12.03</td>
<td>-0.06</td>
</tr>
<tr>
<td><strong>Seed-Specific Coefficients of Risk Aversion</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>β̂_{j, B1}</td>
<td>0.0032</td>
<td>0.0070</td>
<td>-0.0128</td>
<td>0.0129</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b_{j, B1}</td>
<td>-0.0023</td>
<td>0.0071</td>
<td>-0.0129</td>
<td>0.0129</td>
<td>-6.52</td>
<td>0.05</td>
</tr>
<tr>
<td>β̂_{j, B2}</td>
<td>0.0088</td>
<td>0.0057</td>
<td>-0.0129</td>
<td>0.0129</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b_{j, B2}</td>
<td>0.0024</td>
<td>0.0058</td>
<td>-0.0124</td>
<td>0.0151</td>
<td>-9.28</td>
<td>0.04</td>
</tr>
<tr>
<td>β̂_{j, T}</td>
<td>0.0156</td>
<td>0.0112</td>
<td>-0.0217</td>
<td>0.0218</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b_{j, T}</td>
<td>0.0055</td>
<td>0.0171</td>
<td>-0.0249</td>
<td>0.0248</td>
<td>-5.91</td>
<td>0.12</td>
</tr>
<tr>
<td>β̂_{j, S}</td>
<td>0.00002</td>
<td>0.0151</td>
<td>-0.0223</td>
<td>0.0224</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b_{j, S}</td>
<td>-0.0039</td>
<td>0.0125</td>
<td>-0.0230</td>
<td>0.0229</td>
<td>-2.38</td>
<td>0.08</td>
</tr>
<tr>
<td>β̂_{j, H}</td>
<td>0.0032</td>
<td>0.0062</td>
<td>-0.0129</td>
<td>0.0129</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b_{j, H}</td>
<td>-0.0024</td>
<td>0.0063</td>
<td>-0.0131</td>
<td>0.0131</td>
<td>-7.52</td>
<td>-0.03</td>
</tr>
<tr>
<td>β̂_{j, L}</td>
<td>-0.0036</td>
<td>0.0077</td>
<td>-0.0129</td>
<td>0.0125</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b_{j, L}</td>
<td>-0.0061</td>
<td>0.0062</td>
<td>-0.0133</td>
<td>0.0134</td>
<td>-3.03</td>
<td>-0.01</td>
</tr>
</tbody>
</table>

Note: t statistic is for the null that a coefficient of risk aversion based on estimated probabilities, b, is equal to its corresponding true probabilities coefficient, β.

Table 3. Estimation Results from Trait Model with Average Coefficient of Risk Aversion (× 100,000) as Dependent Variable

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.09</td>
<td>3.02</td>
<td>1.13</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td>(2.98)</td>
<td>(1.92)</td>
<td>(1.40)</td>
<td>(1.24)</td>
</tr>
<tr>
<td>Edu</td>
<td>7.00</td>
<td>-1.50</td>
<td>3.66</td>
<td>5.12</td>
</tr>
<tr>
<td></td>
<td>(7.97)</td>
<td>(5.14)</td>
<td>(3.74)</td>
<td>(3.31)</td>
</tr>
<tr>
<td>TLU</td>
<td>8.26</td>
<td>17.41</td>
<td>12.80</td>
<td>12.23</td>
</tr>
<tr>
<td></td>
<td>(21.76)</td>
<td>(14.03)</td>
<td>(10.22)</td>
<td>(9.04)</td>
</tr>
<tr>
<td>Irrland</td>
<td>82.26</td>
<td>-211.62*</td>
<td>-78.85*</td>
<td>-79.51*</td>
</tr>
<tr>
<td></td>
<td>(100.49)</td>
<td>(64.80)</td>
<td>(47.20)</td>
<td>(41.72)</td>
</tr>
<tr>
<td>Bt {0,1}</td>
<td>-85.25</td>
<td>9.33</td>
<td>5.72</td>
<td>26.76</td>
</tr>
<tr>
<td></td>
<td>(64.63)</td>
<td>(41.68)</td>
<td>(30.36)</td>
<td>(26.83)</td>
</tr>
<tr>
<td>Wealth</td>
<td>-50.34</td>
<td>-34.31</td>
<td>-4.80</td>
<td>-44.09*</td>
</tr>
<tr>
<td></td>
<td>(55.18)</td>
<td>(35.58)</td>
<td>(25.92)</td>
<td>(22.91)</td>
</tr>
<tr>
<td>Constant</td>
<td>422.29*</td>
<td>-204.65*</td>
<td>-60.41</td>
<td>-181.68*</td>
</tr>
<tr>
<td></td>
<td>(158.38)</td>
<td>(102.13)</td>
<td>(74.39)</td>
<td>(65.75)</td>
</tr>
<tr>
<td>R-Sqr</td>
<td>0.07</td>
<td>0.37</td>
<td>0.38</td>
<td>0.40</td>
</tr>
<tr>
<td>N</td>
<td>277</td>
<td>277</td>
<td>277</td>
<td>277</td>
</tr>
</tbody>
</table>

Note: Standard errors shown in parentheses. * indicates statistical significance at the 10% level.
Spurious correlations introduced by estimated probabilities are evident in the tightening of the confidence 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. As figure 6 shows, estimated standard errors, as a percentage of estimated coefficients, tend to shrink as we use more restrictive technology models to estimate probabilities. The specification of risk clearly has a major impact on the estimation of risk aversion parameters.

Figure 7 displays interval estimates for the wealth index 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 clearly the use of wealth and correlates thereof in the estimation of probabilities. More generally, this figure reinforces the result that these correlations between wealth and risk aversion can be both muddled and misleading when probabilities are estimated using correlates of wealth.

Lastly, we focus on seed-specific trait models that compare $b_{jt}^{KS}$ and $\beta_{jt}$ for $t = \{B1, B2, T, S, H, L\}$. 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
Figure 8. 90% confidence interval estimates of wealth coefficients in trait model where dependent variables are seed-specific (baseline $[B1, B2]$, truncated $[T]$, stabilized $[S]$, high $[H]$, and low $[L]$) and average coefficients of risk aversion as estimated using true probabilities and estimated probabilities (EP1 with different explanatory variables in probability model)

interval estimates for all six distribution types and for the average over these distributions (i.e., $\hat{\beta}_j$ and $\tilde{b}_j^{KS}$). There are two results worth noting in this figure. First, the estimated wealth coefficients for the true probabilities 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.

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 article 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.

Using data from a field experiment in which probabilities are known, we demonstrate how estimating probabilities can introduce spurious correlation between socio-economic traits and risk preferences. This key result has two important dimensions. First, compared to actual correlations computed with known probabilities, correlations computed with unknown probabilities estimated using common techniques can seriously mislead. Second, comparing correlations across different approaches to estimating probabilities suggests that the illusion of a relationship between risk aversion and socio-economic factors decreases in strength with the flexibility of the
estimated production function. This apparent relationship highlights the need for greater understanding of how production and risk preference specifications influence one another. Only with this understanding can field data be used to test Arrow’s important hypotheses accurately.

We have focused here on problems stemming from our limited knowledge as researchers of the probabilities individuals face when making decisions under risk. Since the simple probabilities in our field experiment are observable to us and to the Indian farmers we surveyed, we have implicitly treated these as objective probabilities. Even in experimental settings, however, individuals may not fully internalize the stated probabilities. Thus, subjective perceptions of probabilities—the focus of many models of behavioral decision-making under risk—become directly relevant to any assessment of risk preferences (see Just 2001). Given the focus of this article this raises an obvious question: does it really matter whether we as researchers can observe objective probabilities if the individuals we study do not either? Establishing correlations between risk aversion and wealth is likely to be even trickier in the presence of subjective probabilities that deviate significantly from their objective counterparts. In such a circumstance, we must rely on observed choices to convey information about both subjective probabilities and risk aversion. Identifying these effects simultaneously is a real feat. Additionally, if probability perceptions differ systematically according to wealth or its correlates, spurious correlation between risk aversion and wealth will continue to be a problem even under strict laboratory settings. This possibility that subjective perceptions in the laboratory are correlated with wealth seems less likely than the production estimation problem we describe, where correlation with wealth is a fundamental characteristic of the risk faced by the decision-maker. Nonetheless, cleverly designed experiments can allow estimation of risk aversion coefficients even if probabilities are distorted in some unknown way (e.g., Wakker and Denefle 1996).

The nature of the problem we have highlighted here limits our hope for ready-made remedies. Because this is more than a technical econometric problem such as errors in variables, it cannot be remedied by sophisticated econometric techniques alone. If the ultimate objective is to test Arrow’s risk aversion-wealth hypothesis, one possible remedy is to find socio-economic variables that directly shape the probabilities in individuals’ profit functions but are uncorrelated with wealth. If such variables existed, one could use the first set to estimate the probabilities implicit in profit/production functions and still use wealth and/or other variables in the second set to test for correlations with risk aversion. It is hard for us to imagine examples of two such sets of variables. A more hopeful remedy may exist further upstream in the research process. An appreciation of the problems highlighted in this article should shape the design of data collection efforts. In particular, data collection should aim to solicit individuals’ subjective risk preferences through carefully designed, pretested and refined survey questions and field experiments. Binswanger (1982) advocated using experimental approaches to help pin down the nature of distribution of risk over two decades ago. Given the limitations of field experiments (e.g., validity outside a contrived experiment context), however, these are likely to be most useful when combined thoughtfully with other methodologies. Work on entrepreneurship, for example, has taken some useful methodological steps in combining survey and experimental techniques to examine risk aversion (e.g., Dohmen et al. 2005; Low and MacMillan 1988). Ultimately, if we wish to know something about how risk preferences and wealth are correlated, we must be fully aware of the confounding factors common in empirical risk research, including statistical artifacts introduced through estimated probabilities, and willing to invest in more careful and innovative data collection methods.

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References


