Indian Farmers' Valuation of Crop Yield Distributions:
Will poor farmers value 'pro-poor' seeds?

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ABSTRACT: Potential poverty traps among the rural poor suggest a need to reduce poor farmers' vulnerability by stabilizing crop yields and limiting yield losses. Advances in agricultural biotechnology enable breeders to address this need more directly than ever before with crops that reduce production risk by tolerating climate fluctuation or resisting biotic stresses. Will poor farmers who could benefit most from less vulnerability choose to purchase such risk-reducing seeds? I use data from a household survey and experiment involving farmers in India to infer their valuation of changes in the mean, variance, and skewness of yield distributions. I conclude that these farmers value increases in expected yield in the yield distribution but seem indifferent about changes in higher moments of the distribution. Farmer traits such as wealth and risk exposure affect farmers' valuation of changes in yield distributions only mildly.

JEL: C9–Design of Experiments, D8–Uncertainty, O1–Economic Development, Q1–Agriculture

Keywords: Poverty, Risk, Biotechnology, Experimental Economics

1 INTRODUCTION

Uncertainty is a defining feature of poverty. The poor, especially in poor countries, lack access to resources and institutions that can reduce routine fluctuations in consumption, income or wealth and moderate catastrophic asset or health shocks. Consequently, the dynamics of poverty and vulnerability have received much recent attention (see Dercon 2004, Wood 2003, World Bank 2000). Studies that find empirical evidence for poverty traps among the rural poor (e.g., Barrett, et al. 2001, Carter and May 1999, Dercon 1998, Lybbert, et al. 2004, Zimmerman and Carter 2003) suggest a need to reduce poor farmers' vulnerability by stabilizing crop yields and limiting yield losses.

Crop yields are risky because they depend on weather (especially temperature and the amount and timing of precipitation), biotic stresses (pests and diseases), and the optimal timing of inputs (fertilizers, pesticides and weeding), all of which are stochastic (Roumasset 1976). Advances in agricultural biotechnology enable breeders to reduce farmers' exposure to all three of these sources of risk more directly than ever before. Soon, crops that tolerate drought and extreme temperatures or that resist disease, viruses, bacteria and insects will likely be widely available to farmers. The welfare gains for poor farmers who are particularly vulnerable to routine climate fluctuations and catastrophic crop losses could be substantial. Of course, realizing these welfare gains requires vulnerable farmers to adopt these new seeds. Will poor farmers who could benefit most from less vulnerability choose to purchase such risk-reducing seeds?

Even poor farmers will pay a significant premium for seeds with higher expected yield (David and Sperling 1999), but farmers may not be as quick to pay more for seeds that reduce risk. The relative benefit of such a seed is a function of the targeted stochastic variable (e.g., weather, pests, etc.) and is hence also stochastic. Thus, the advantage of these seeds will not be apparent every season, which may slow learning. Since these seeds will largely be developed and delivered by the private sector, risk reducing traits will likely carry a price premium, which will largely determine the riskiness of the net returns of the seeds (Binswanger 1979). Thus, farmers may conceivably lose money by adopting pest resistant seeds during seasons with low pest loads, for example, making adoption potentially erratic. This may be especially true for poor farmers who are unable to survive "a bad year or two in an optimal policy sequence" (Lipton 1968, p. 335).

The objective of this paper is to evaluate whether Indian farmers value risk-reducing seeds. I use data from a household survey and experiment involving farmers in Tamil Nadu state, India, to infer their valuation of changes in the mean, variance, and skewness of yield distributions. I conclude that the Indian farmers in the study value increases in expected yield arising from unconditional upward shifts in the yield distribution but seem indifferent about changes in higher moments of the yield distribution. Farmer traits such as wealth and risk exposure affect farmers' valuation of changes in yield distributions only mildly. After presenting the data analysis, I discuss some of the limitations of the experimental methodology used to elicit farmers' valuation of payoff distributions in order to facilitate interpretation of these findings.

2 BACKGROUND

My working definition of 'pro-poor' seeds consists of two simple parts. First, 'pro-poor' seeds must be relevant to the poor. Poor farmers must presently or potentially grow the crop. This implies low initial investment, low fixed costs of production and relatively simple (albeit possibly labor-intensive) management practices. In the case of a food crop, poor consumers should consume the crop. Second, 'pro-poor' seeds must confer some benefit relative to other seeds that addresses problems commonly faced by the poor. To date, these 'pro-poor' benefits have been of three sorts: (a) higher expected yield to address problems such as macro-nutrient deficiency, lack of market entitlements, and chronic abiotic stresses such as soil salinity and low soil fertility, (b) lower yield risk via better yield stability (i.e., lower variance) or lower downside yield fluctuation (i.e., higher skewness) to address problems such as food security and income stability, and (c) higher micro-nutrient content to address micro-nutrient deficiency problems.

Lipton and Longhurst (1989) carefully dissect the impact of modern varieties on the poor. Their contrast of the goals of plant science and those of poor farmers highlights why higher moments of yield distributions matter to the poor:

> Breeders see quantity (as indicated by yield) – and, some way behind, quality – as overwhelmingly their main goals…A poor farmer would still wonder about three missing items. They are stability, sustainability, and cross-crop effects. [M]ost breeders may well see them as long-term components of yield. Indeed, a lower risk of downward fluctuation in crop output, or of its long-run decline, is ultimately a form of increased yield. However, poor farmers also value stability as such independently of yield, and even at its expense. They cannot afford to take big risks. (Lipton and Longhurst 1989, pp 28-29)

Yield stability may be particularly important to poor farmers in rainfed areas where variable rainfall and inherently unstable food production drive poverty dynamics (DeVries and Toenniessen 2001).

Recent advances in science have enabled breeders to improve yield stability through resistance to biotic or climatic stresses. Since the mid-1980s, yield stability has been an increasingly important component of traditional plant breeding (Traxler, et al. 1995). Thanks to biotechnological advances even previously-intractable stability and micro-nutrient problems can now be addressed (Conway 1997, DeVries and Toenniessen 2001). Specific recent examples include mosaic-resistant cassava in Uganda, Mendel Biotechnology's 'drought protection' technology, disease-resistant banana, virus- and pest-resistant sugar cane, and virus-resistant sweet potato (Wambugu 1999). The *Bt* gene found in the *bacillus thurengensis* bacteria provides resistance to boring pests and can also confer distinctly pro-poor benefits by protecting farmers from catastrophic crop losses in high pest load years. Small farmers indeed appear to benefit from the *Bt* technology (Ismael, et al. 2002, Thirtle, et al. 2003).[1] Gene-based technologies such as these can also facilitate adoption and use, making the benefits more accessible to poor farmers.

Farmers in developing countries increasingly procur seeds from the private sector for both cash and subsistence crops (David and Sperling 1999, Pray and Fuglie 2000, Tripp and Pal 2000). They are also generally a more heterogeneous lot than their developed country counterparts, ranging from large-scale commercial to small-scale semi-commercial to subsistence (Cromwell, et al. 1992), which makes the spread of even seemingly-superior seed varieties difficult to predict (David and Sperling 1999). Differences between farmers' resource endowment, management strategy and market situation affect their valuation of seed production traits (yield potential and stability), consumption traits (taste, color, texture), economic traits (early maturity, market demand, storability), and cultural traits (beliefs, rituals) (Cromwell, et al. 1992, Louwaars, et al. 1997).

Seed demand generally tends to be price inelastic. Indeed, several other variables affect farmers seed purchase decisions more than price. Physical access to an appropriate quantity of quality seeds, the timing of availability, and information about seed are often more important than the seed price (Cromwell, et al. 1992, Heisey and Brennan 1991, Rohrbach and Malusalila 2000,

[1] Although some worry that poor farmers who become dependent on the *Bt* gene for protection against pests will be particularly hurt if (when) pests develop resistance to *Bt* (Lipton 2001).

Tripp 2001). The yield advantage, seed rate, and production and market risk of a seed also directly influence farmers' decision to adopt a new seed (Feder, et al. 1985).[2] While this may be true in general, price remains a critical issue for poor farmers. These vulnerable farmers tend to be more sensitive to seed price than other farmers because they devote a larger portion of their less input-intensive production costs to seed purchases. Thus saving seed – a viable option for many poor farmers given their opportunity costs and management strategies – often provides a cheaper, if inferior, substitute to seeds purchased from dealers (Louwaars, et al. 1997).

3 MODEL

How should farmers value changes in a seed's yield distribution? How does a farmer's wealth affect his valuation of these yield distribution changes? This section presents a stylized, two-season expected utility model to highlight why different farmers might differ in their valuation of distributions and why yield stability and lower downside yield risk might disproportionately benefit the poor.

Suppose that in the current season farmers receive a net income stream from existing assets (w_i) and have the option of growing an additional seed variety. To isolate valuation of the yield distribution from any scale effects, assume all farmers face the same discrete planting decision: whether or not to plant the new seed on a single acre. Assume further that farmers' wealth in the second season is determined by first season income according to a commonly known recursion function $f(.)$. Finally, assume that markets for inputs, output and consumption goods are complete

[2] Other general determinants of technology adoption are equally relevant. Farm characteristics such as size, topography and soil quality are important adoption determinants, as are farmer characteristics such as gender (Cameron 1999) and education (Pitt and Sumodiningrat 1991), and household wealth and size. Farmers' perceptions about the complexity and relative risk of a technology likewise affect adoption (Adesina and Baidu-Forson 1995, Batz, et al. 1999). Information about the value of a new technology is paramount, so learning-by-doing (Cameron 1999), learning from others (Foster and Rosenzweig 1995), and – to a lesser extent – formal extension are critical adoption determinants. Market imperfections often imply differences in transactions costs (Holloway, et al. 2000), access to credit (Feder, et al. 1985) and capacity to mitigate and manage risk (Batz, et al. 1999), which can all significantly affect the pattern of adoption among different farmers.

and that farmers are price-takers in these markets, a separability assumption that implies that maximizing the utility of total net income and maximizing the utility of consumption generate the same optimal production decisions. Farmers' decision whether or not to plant the seed is thus:

$$\max_{d_i=\{0,1\}} V(\pi_{i1},\pi_{i2}) = u(\pi_{i1}) + \delta u(\pi_{i2})$$
$$s.t.\ \pi_{i1} = (1-d_i)w_i + d_i(y(\mathbf{z},\varepsilon) - p + w_i)$$
$$\pi_{i2} = f(\pi_{i1})$$

where V(.) is the intertemporal utility function, u(.) is a strictly monitonically increasing utility function, $\delta<1$ is the discount factor, π_{it} is total net income in season t, $d_i=1$ if farmer i plants the seed with $d_i=0$ otherwise, y(**z**,ε) is the net yield function for the seed measured in per acre monetary units net of all inputs except the seed, **z** is a vector of inputs, ε captures stochastic yield risk with a cumulative density function H(ε), and p is the purchase price of the new seed. Net yield y(.) is net of all inputs except the seed in order to isolate the seed price, p. To isolate the seed purchase decision further, w_i captures all other income or transfers net of any associated costs. Farmers differ only in w_i to emphasize how wealth affects valuation.

Assume that the new seed has constant returns to scale and that farmers exhibit no systematic technical or allocative inefficiencies. This implies that the optimal input vector per acre (**z***) is the same for all farmers, as is the optimal stochastic net yield function y=y(ε|**z***)=y(ε). With this assumption the problem becomes

$$\max_{d_i=\{0,1\}} (1-d_i)V\left(w_i, f(w_i)\right) + d_i\, E\left[V\left(y(\varepsilon) - p + w_i, f(y(\varepsilon) - p + w_i)\right)\right]$$

where E is the expectation operator. This discrete planting decision involves a maximum willingness-to-pay (p*) defined as

$$V\left(w_i, f(w_i)\right) = E\left[V\left(y(\varepsilon) - p^* + w_i, f(y(\varepsilon) - p^* + w_i)\right)\right] \tag{1}$$

and the decision rule: purchase and plant if and only if p≤p*.

Yield stability and lower downside yield risk are considered 'pro-poor' because many poor farmers subsist precariously close to critical survival thresholds. To capture this important, if normally implicit, rationale for 'pro-poor' seeds, suppose that the wealth recursion function *f* (.) takes the simple form

$$\pi_2 = f(\pi_1) = \begin{cases} \pi_1 & if\ \pi_1 > \pi^0 \\ 0 & if\ \pi_1 \leq \pi^0 \end{cases}$$

Provided that farmers perceive these bifurcated wealth dynamics, the intertemporal utility function V(.) is directly shaped by *f* (.). To focus specifically on these threshold effects, assume that the current utility function is linear, defined as $u(\pi)=\pi$, so that intertemporal utility is[3]

$$V\left(\pi_{i1}, \pi_{i2}\right) = V\left(\pi_{i1}\right) = \begin{cases} \pi_{i1}(1+\delta) & if\ \pi_{i1} > \pi^0 \\ \pi_{i1} & if\ \pi_{i1} \leq \pi^0 \end{cases}$$

The discontinuity in this intertemporal utility function implies that farmer i values that portion of the net yield distribution below $y_i^0=\pi^0+p-w_i$ differently than that above y_i^0 because any yield $y>y_i^0$ pushes him safely above π^0. In what follows, assume that p is small relative to π^0 and w_i so that $y_i^0 \approx \pi^0 - w_i$. Given that H(ε) is the cdf of ε and y=y(ε), a cdf for y can be derived as G(y)=G(H(ε)). For farmer i with w_i, the probability θ_i that his total net income after planting the seed will be below the trap threshold is therefore given by

$$\theta_i = \Pr(y \leq \pi^0 - w_i) = \Pr(y \leq y_i^0) = G(y_i^0)$$

If all farmers are offered the same yield distribution, $y^0_{RICH} < y^0_{POOR}$ and $\theta_{RICH} < \theta_{POOR}$ as long as there is no price discrimination between farmers and G(y) is strictly increasing (locally). Simply put, a poor farmer simply cannot sustain much of a yield decline without dropping below the wealth threshold. Define the expected value of the yield distribution below and above y_i^0, respectively, as

[3] The general results of this simple model hold for standard concave utility functions as well. Linear current utility simply serves to focus attention on the effects of wealth thresholds on farmers' valuation of payoff distributions.

$$y_i^L = E\left[y \middle| y \le y_i^0\right] = \int_{-\infty}^{y_i^0} y(\varepsilon)dG(y)$$
$$y_i^H = E\left[y \middle| y > y_i^0\right] = \int_{y_i^0}^{\infty} y(\varepsilon)dG(y)$$

such that

$$E\left[y\right] = \int_{-\infty}^{\infty} y(\varepsilon)dG(y) = \theta_i y_i^L + (1-\theta_i)y_i^H$$

We can now solve for farmers' valuation of a yield distribution. Consider two cases: [1] $w_i > \pi^0$ and [2] $w_i \le \pi^0$.

[Case 1] $\underline{w > \pi^0}$: As in equation (1), farmers' valuation of the net yield function is given by their maximum willingness-to-pay, p_1*, as defined by:

$$\begin{aligned} w_i(1+\delta) &= \theta_i\left(y_i^L - p_1 {*} + w_i\right) + \left(1-\theta_i\right)\left(y_i^H - p_1 {*} + w_i\right)\left(1+\delta\right) \Leftrightarrow \\ p_1 {*} &= \left[\theta_i y_i^L + \left(1-\theta_i\right)\left(1+\delta\right)y_i^H - w_i\delta\theta_i\right]\left(1+\delta\left(1-\theta_i\right)\right)^{-1} \\ p_{1|\theta=0} {*} &= y_i^H = E\left[y\right] \\ p_{1|\theta=1} {*} &= y_i^L - w_i\delta = E\left[y\right] - w_i\delta \end{aligned} \tag{2}$$

Given any yield distribution a farmer may be solidly out of the trap's reach if w_i is high enough that $G(y_i^0)=\theta_i=0$, in which case $p_{1|\theta=0}{*} > p_1{*}$. Conversely, for farmers with w_i near π^0, the same yield distribution could, if production requires substantial and costly inputs (e.g., pesticides),[4] also produce $\theta_i=1$, in which case valuation falls to $p_{1|\theta=1}{*} < p_1{*} < p_{1|\theta=0}{*}$.

[Case 2] $\underline{w \le \pi^0}$: Desperately poor farmers are doomed unless saved by the double good fortune of a good seed and good harvest. Not surprisingly, these destitute farmers value yield distributions quite differently. Their valuation, p_2*, is defined as:

[4] Recall that y(.) is defined as returns per acre net of all inputs except the seed.

$$
\begin{aligned}
w_i &= \theta_i\left(y_i^L - p_2{*} + w_i\right) + \left(1-\theta_i\right)\left(y_i^H - p_2{*} + w_i\right)\left(1+\delta\right) \Leftrightarrow \\
p_2{*} &= \left[\theta_i y_i^L + \left(1-\theta_i\right)\left(1+\delta\right) y_i^H + w_i\delta\left(1-\theta_i\right)\right]\left(1+\delta\left(1-\theta_i\right)\right)^{-1} \\
p_{2|\theta=0}{*} &= y_i^H + w_i\delta\left(1+\delta\right)^{-1} = E\left[y\right] + w_i\delta\left(1+\delta\right)^{-1} \\
p_{2|\theta=1}{*} &= y_i^L = E\left[y\right]
\end{aligned}
\tag{3}
$$

which is identical to $p_1{*}$ in (2) except that w_i is multiplied by $(1-\theta_i)\delta$ instead of $(-\delta)$. Unlike those above the threshold, these farmers value a yield distribution not just for current season earnings, but also for the escape it could provide next season. Again, if the net yield distribution is high enough and w_i is close to π^0, it might be true that $\theta_i=0$. The converse, $\theta_i=1$, may again be true if w_i is far below π^0, in which case valuation falls to $p_{2|\theta=1}{*}<p_2{*}<p_{2|\theta=0}{*}$.

For purposes of discussing this model, it will help to classify farmers as three types: *desperately poor*, *poor*, and *non-poor*. Given the severity of the trap in this model, any farmer threatened by the threshold π^0 ($\theta>0$) qualifies as poor. Of those with $\theta>0$, the *desperately poor* are those with $w<\pi^0$, and the *poor* are those with $w>\pi^0$. The *non-poor* are a safe distance from the trap with $w>>\pi^0$ such that $\theta=0$. What does the solution in (2) and (3) suggest about how these three types of farmers value the stabilized or truncated yield distributions that characterize 'pro-poor' seeds? For starters, note that

$$
\left.\frac{\partial p_1{*}}{\partial\theta}\right|_{Non-poor} = 0, \quad \left.\frac{\partial p_1{*}}{\partial\theta}\right|_{Poor} < 0, \quad \left.\frac{\partial p_2{*}}{\partial\theta}\right|_{Desperate} < 0
$$

Since stabilized and truncated distributions benefit those concerned about downside risk (θ) the *poor* and *desperately poor* in this model primarily benefit from such 'pro-poor' seeds.

More specifically, the *non-poor* are risk neutral. This implies that the *non-poor* value only the first moment of the net yield distribution and would not value a stabilized distribution at all. They would value a truncated yield distribution, but only because it implies a higher E[y]. The *poor* are risk averse, implying that they value improvements in higher moments. A stabilized distribution that reduces θ would appeal to the *poor* (except in the unlikely case that $\theta>0.5$). In contrast to the *non-poor*, the *poor* would value a truncated distribution for both its increased E[y] and its lower θ. The *desperately poor* in this model are (rationally) risk loving because a yield distribution offers them a 'nothing-to-lose' gamble – a possible escape from imminent collapse. Like the *poor*, they would value a truncated distribution for both higher E[y] and lower θ. Those with $\theta<0.5$ would also value a stabilized distribution. For the *desperately poor* with $\theta>0.5$, however, a stabilized distribution actually increases θ and lowers p_2*.

In sum, the poor are not all alike – especially when there are severe wealth thresholds that lead to extreme poverty traps. Provided that farmers perceive these wealth dynamics, their valuation of yield distributions can be shaped dramatically by these thresholds. While the 'poor' are surely a heterogeneous lot, it is also true that many poor farmers do hover precariously close to wealth thresholds. For many, a series of bad harvest draws can quickly make even the kind of draconian subsistence threshold captured in this model a relevant threat. All such farmers should warmly welcome 'pro-poor' seeds that reduce downside risk through stabilized or truncated distributions.

4 DATA

To assess farmers' valuation of stabilized and truncated crop yield distributions, this paper uses data from the Salem and Perambalur districts of Tamil Nadu state, India. Tamil Nadu state was selected because Tamil Nadu Agricultural University agreed to provide the necessary administrative and logistical support as a collaborating institution in the second round of the Agricultural Biotechnology Support Program, which funded this research. Salem and Perambalur districts were selected because these districts constitute Tamil Nadu's 'cotton belt.' Some cotton farmers in this area have adopted *Bt* cotton – mostly the MECH 162 and 184 varieties of Monsanto-Mahyco's Bollguard™ cotton – which protects against losses due to boring pests. These farmers' choice to adopt *Bt* cotton partly reveals their ex ante valuation of the *Bt* gene. But, in India, the *Bt* gene seems to protect cotton from chronic pest losses and thus does more than simply truncate the cotton yield distribution (Qaim and Zilberman 2003). *Bt* cotton thus imperfectly fits the analysis in this paper and is not the primary focus of the paper.

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. A map of study area is shown in Figure 1. With the villages selected, the research team used choice-based stratified sampling to ensure the participation of *Bt* cotton farmers and other farmers. The team constructed a list of all the *Bt* cotton famers in a village and randomly selected *Bt* cotton farmers, then randomly selected other farmers with the assistance of the village administrative officer.

The research team collected data from selected farmers 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. Knowing that the experiment would provide the crux of the analysis, I designed the experiment according to accepted experimental economic principles (see Davis and Holt 1993, ch.8), then pre-tested with farmers in the field to ensure the experiment was comprehensible to farmers.

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, 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.[5]

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.

While the design of the experiment aimed to elicit farmers' valuation as accurately as possible, there were two systematic 'game effects' that influenced the high-stakes WTP of many farmers. First, many farmers who did not purchase the seed in one season would increase their WTP in the next season to increase their chances of playing the game.[6] Second, many farmers who played

[5] 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).

[6] When questioned about this tendency, most expressed a distinct preference for playing the game over not playing the game. Some associated this preference with their proclivities as farmers, explaining that a farmer who fails to plant seed in a given season is certain not to succeed. For others, the preference to play was simply due to playing

the game and had a positive (negative) harvest payoff in one season often increased (cautiously lowered) their bids in the following season. In the econometric analysis of the next section, I control for these two game effects: a $Play_{it}$ variable that controls for whether a farmer purchased the seed in the immediately preceding season and a $Earn_{it}$ variable that captures the farmer's earnings in this preceding season.

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 abstractness, the experiment had to be based clearly in a farming context. Only within this context would farmers fully understand the experiment. Since all participants in the experiment were farmers and since the primary use for the data is drawing inferences about farmers' valuation of yield distributions, abandoning some abstractness in favor of context is easily defensible. Still, a core challenge in designing the experiment was striking an appropriate balance between abstractness and context.

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' valuation of distribution changes are desired, all four orderings begin and end with the Base distribution, B. Throughout, I use the average of farmers' high-stakes WTP for the first B and the second B to represent WTP for B. Also, to simplify the presentation I exclude the L distribution and focus just on the B, H, S, and T distributions for part of the analysis in the paper. These four distributions were preceded by two simplified practice distributions to allow farmers to understand the structure of the experiment.

being more enjoyable than not playing. Whatever the explanation, it is clearly important to control for this game effect before interpreting farmers' WTP.

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. 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.' I conduct the econometric analysis with and without these farmers.

Figure 2 shows the marginal (top panel) and cumulative (bottom panel) probability distributions for the B, H, S, and T distributions of the experiment (note that the L distribution that is excluded here is B shifted down Rs30). The top panel also shows 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. These distributions were also chosen so that key hypotheses about farmers valuation of higher moments of yield distributions could be tested. Specifically, these distributions represent an increase in EV that leaves σ and skewness unchanged (H), a decrease in σ that leaves EV and skewness unchanged (S), and an increase EV due to an increase in skewness that leaves σ relatively unchanged (T). From the cumulative probability distributions in the bottom panel of Figure 3, the first-order stochastic dominance ($>_{FSD}$) properties of these distributions are: $H>_{FSD}B$, $T>_{FSD}B$, $T>_{FSD}S$. S weakly second-order stochastic dominates B ($S\geq_{SSD}B$). There is no dominance relationship for H, T and H, S.

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. 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.[7] 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. Finally, farmers' WTP for B and S appear surprisingly indistinguishable for the average farmer, whose WTP is notably higher for T and H. 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.

Since the focus of this paper is farmers' valuation of changes in crop yield distributions, additional descriptive statistics on farmers' bids in the experiment are insightful. One can describe these bid data graphically by sorting the bids for each distribution in descending order and then graphing these ordered data. Such a graph represents a simple demand curve. Graphs of the ordered bid data are shown in Figure 4. The purchase decision in the experiment was discrete, not continuous, by construction so that farmers either purchased the seed or did not. Thus the horizontal axis in Figure 4 is the number of farmers who purchased a particular seed at a given price.

Consider first the curve for the Base (B) distribution with EV_B=Rs50. Ignoring the upper and lower tails of the curve, this curve has a shallow slope centered on the Rs45 mean bid (Table 1). The demand curve for B is nearly indistinguishable from the demand curve for S. This is surprising since $EV_B=EV_S$=Rs50 but $\sigma_S=23.8<40.8=\sigma_B$. This preliminary evidence suggests that farmers may not value lower yield variance. The demand curve for T is uniformly higher than both the S and B

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

curves, and the curve for H is uniformly the highest curve. This confirms that farmers are indeed responsive to EV changes, but one can infer little more about farmers' valuation of distribution changes from these curves. Consider the difference between the curves of B and T. While it is clear that farmers are willing to pay a premium for T, it is not clear whether this premium is a function of all three moment changes – a higher EV, a lower variance and a higher skewness ($sk_T=1>0=sk_B$, implying lower downside risk) – or only of a higher EV. To assess how these higher moments affect farmers' valuation, one must move beyond descriptive statistics.

5 ANALYSIS

In the econometric analysis that follows, I focus on three sets of models. The first set focuses on 'treatment' effects and estimates the mean valuation of the typological distributions of the experiment, both independently and relative to distribution B. The second set of models focuses on 'moment effects' and estimates farmers' valuation of moments of the payoff distributions. The third set of models focuses on 'farmer' effects and estimates how farmer traits affect farmers' valuation of payoff moments. This third set of models requires wealth and risk exposure indices, which I also discuss and estimate in this section.

Treatment Effects Models: The models that isolate the treatment effects are of the form:

$$WTP_{it} = f\left(\mathbf{t}_t, \mathbf{g}_{it}, \mathbf{f}_i\right) + \varepsilon_{it}$$

where WTP_{it} is farmer i's high-stakes bid or willingness-to-pay for distribution t, $\mathbf{t}_t$ is a vector of treatment dummies with a 1 corresponding to distribution t and 0's elsewhere, $\mathbf{g}_{it}$ is a vector of 'game effect' variables that control for the (artificial) effects of specific features of the experiment on bidding behavior, $\mathbf{f}_i$ is a vector of farmer dummies with a 1 corresponding to farmer i that controls for farmer fixed effects so that treatment effects are isolated,[8] and ε_{it} is an error term distributed $N(0,\sigma_{\varepsilon i}^2)$ where the disturbance variance $\sigma_{\varepsilon i}^2$ allows for heteroscedasticity between (but not within) farmers.

I consider three specifications of this generic treatment effects model. The first is:

$$WTP_{it} = \alpha_B + \alpha_H H_t + \alpha_S S_t + \alpha_T T_t + \alpha_1 Play_{it} + \alpha_2 Earn_{it} + \boldsymbol{\varphi}_\mathbf{1}'\mathbf{f}_\mathbf{i} + \varepsilon_{it}$$

which uses farmers' absolute WTP as the dependent variable. Independent variables consist of a constant, treatment dummies (H, S, T), two 'game effects' variables (Play and Earn, explained below), and farmer fixed effects (**f**). The coefficients on the constant and on the treatment dummies are the coefficients of primary interest. The coefficient α_B indicates the conditional mean WTP for B, and $(\alpha_B+\alpha_H)$, $(\alpha_B+\alpha_S)$ and $(\alpha_B+\alpha_T)$ indicate the conditional mean WTP for H, S and T, respectively. The first game effects variable ($Play_{it}$) is a 'play' dummy variable that is 1 if the farmer's bid in the practice season immediately preceding the high-stakes season of treatment t was such that he purchased the seed (i.e., his bid was greater than or equal to the randomly drawn seed cost) and received an uncertain payoff. The second game effect variable ($Earn_{it}$) captures the farmer's earnings in the immediately-preceding season.

In expected utility parlance, the conditional mean WTP estimates – α_B, $(\alpha_B+\alpha_H)$, $(\alpha_B+\alpha_S)$, and $(\alpha_B+\alpha_T)$ for B, H, S, and T, respectively – represent the corresponding mean certainty equivalents.[9] Furthermore, the mean risk premium is approximately the difference between the EV and WTP for these distributions and can be computed as $RP_B=50-\alpha_B$, $RP_H=80-(\alpha_B+\alpha_H)$, $RP_S=50-(\alpha_B+\alpha_S)$, and $RP_T=65-(\alpha_B+\alpha_T)$, respectively. The joint null hypothesis that tests for risk neutrality based on EV is therefore:

$H1_0$:	$\alpha_B=50=EV_B$	$H1_A$:	$\alpha_B<50$	[joint EV risk neutrality]
	$\alpha_S=0=\Delta EV_S$		$\alpha_S>0$	
	$\alpha_H=30=\Delta EV_H$		$\alpha_H<30$	

[8] Recall that there are two high-stakes bids for B and one high-stake bid for H, S, and T elicited from each farmer.
[9] Since the experimental distributions are over Rupee payoffs, this is true provided second order effects involving u'(.) are relatively small.

$$\alpha_T=15=\Delta EV_T \qquad \alpha_T<15$$

where $\Delta EV_t=EV_t-EV_B$.

Stochastic dominance detection is an important heuristic in the process of decision making under uncertainty (Kahneman and Tversky 1979).[10] Dominance detection can be tested easily with this specification. Based on the first-order stochastic dominance ($>_{FSD}$) relationships $T>_{FSD}B$, $T>_{FSD}S$, and $H>_{FSD}B$, the following joint hypothesis tests for the detection of FSD:

$$\begin{array}{llll} H2_0: & \alpha_T=0 & H2_A: & \alpha_T>0 \\ & \alpha_T=\alpha_S & & \alpha_T>\alpha_S \\ & \alpha_H=0 & & \alpha_H>0 \end{array} \qquad \text{[FSD detection]}$$

The hypothesis that tests for lower variance valuation simultaneously tests for detection of weak second-order stochastic dominance:

$$H3_0: \quad \alpha_S=0 \qquad H3_A: \quad \alpha_S>0 \qquad \text{[lower variance valuation]}$$

which tests whether farmers are willing to pay a premium for a decrease in variance that is isolated from a change in EV.

The second and third specifications that focus on treatment effects differ only in their dependent variable:

$$\Delta WTP_{it} = \delta_S + \delta_H H_t + \delta_T T_t + \delta_1 Earn_{it} + \boldsymbol{\varphi}_2{}'\mathbf{f}_i + \varepsilon_{it}$$
$$\Delta wtp_{it} = \delta_S{}^{\circ} + \delta_H{}^{\circ} H_t + \delta_T{}^{\circ} T_t + \delta_1{}^{\circ} Earn_{it} + \boldsymbol{\varphi}_3{}'\mathbf{f}_\mathbf{i} + \varepsilon_{it}$$

where Δ indicates farmer i's *incremental* willingness-to-pay for distribution t. In order to infer a farmer's valuation of changes in a yield distribution, we must assess how much more the farmer is willing to pay for one distribution over another. The experiment instructions clearly cast distribution B as the benchmark distribution and H, S and T as modifications of this benchmark, making the relevant increment the difference between a farmer's bid for B and his bid for H, S and T. Thus,

[10] Dominance heuristics are especially important in the 'editing stage' of the decision-making process in which an individual simplifies the problem he faces (Kahneman and Tversky 1979).

$\Delta WTP_{it}=WTP_{it}$-avg[WTP_{iB}] and $\Delta wtp_{it}=\Delta WTP_{it}$/avg[$WTP_{iB}$].[11] Using ΔWTP_{it} and Δwtp_{it} instead of WTP_{it} as the dependent variable properly focuses the analysis on farmer-specific, incremental valuation of changes in yield distributions.

The estimated constant in these specifications represents the mean ΔWTP or Δwtp for S. Thus, ($\delta_S+\delta_H$) and ($\delta_S^{\circ}+\delta_H^{\circ}$) represent the mean ΔWTP and Δwtp for H, and ($\delta_S+\delta_T$) and ($\delta_S^{\circ}+\delta_T^{\circ}$) represent the mean ΔWTP and Δwtp for T. Hypotheses for testing risk neutrality and dominance detection with these specifications are simple extensions of H1 and H2 above. Hypotheses for testing variance and skewness valuation are also natural extensions of H3 and H4 but merit explicit statements:

$H3_0$':	$\delta_S=0$	$H3_A$':	$\delta_S>0$	[Δ valuation due to lower var.]
$H3_0$'':	$\delta_S^{\circ}=0$	$H3_A$'':	$\delta_S^{\circ}>0$	[%Δ valuation due to lower var.]

In estimating these three treatment effect models, I assume that the variance of the disturbance term, $\sigma_{\varepsilon i}^2$, may be different for each farmer i. That is, the estimation of these models imposes homoscedasticity within farmers but allows for heteroscedasticity between farmers. In general, allowing for heteroscedasticity between farmers is appealing for the same reasons farmer fixed-effects are appealing. To illustrate more specifically why different farmers likely have different $\sigma_{\varepsilon i}^2$, consider some farmers' tendency to bid in Rs5 increments. Though the experiment imposed no restrictions on farmers' bids, about one third of the farmers bid exclusively in Rs5 increments (i.e., Rs35, 40, 45, etc.), one third bid mostly in Rs5 increments, and one third – undeterred by the 'roundness' of Rs5 increments – bid in increments of Rs1. Because his bids are more discretized, a farmer who bids exclusively in Rs5 increments almost surely has a larger $\sigma_{\varepsilon i}^2$ than one who bids in

[11] Recall that in the experiment, farmers bid on B, then on the other distributions (in four different orderings), then again on B. Averaging farmers' initial high-stakes bid for B with their final high-stakes bid for B controls for changes in farmers' valuation of B that might have occurred as their understanding increases over the course of the experiment.

Rs1 increments.[12] White (1980) standard errors are thus computed throughout to allow for between, but not within, farmer heteroscedasticity.

Table 2 displays estimation results for these treatment effect models with farmer-fixed effects and standard errors corrected for within-farmer heteroscedasticity. The top panel displays results for all farmers. The bottom panel displays results for farmers who understood the experiment, which excludes the 16% who reported they had understood the experiment 'with some confusion,' 'poorly' or 'very poorly.' At the 10% level (one-sided), we reject the joint null of risk neutrality based on EV (H1) for all farmers and for those who understood. We also easily reject the null of FSD detection (H2) for both samples. Farmers clearly detected the obvious dominance relationships $T>_{FSD}B$, $T>_{FSD}S$, and $H>_{FSD}B$. Based on the coefficients on S, the test of lower variance valuation (H3) indicates that farmers' valuation of lower variance appears to be zero on average. This confirms statistically what is true graphically in Figure 3: the demand curves for S and B are indistinguishable. As farmers' maximum WTP, p_1* is approximately their Certainty Equivalent (CE), where Ey-CE=Risk Premium (RP).[13] Thus, Ey-RP=p_1* and p_1*<p_2*=Ey.

The results for the ΔWTP model indicate a failure to reject H3'. Indeed, whether all farmers or only farmers who understood are included δ_S is negative, implying that farmers actually pay *less* for the lower variance of S. That is, they seem to value the lower downside risk *less* than the potential upside gain they sacrifice to get it. Results from the Δwtp model support this finding.

Moment Effects Model: The model that isolates farmers' valuation of the first three moments of the payoff distribution is:

[12] An analog exists in domestic labor surveys: workers who report working 38 hours per week are generally reporting hours worked more accurately than those who report 40 hours per week, many of whom actually worked a few hours more or less than 40 hours. Whether this pull comes from a general preference for such increments (anecdotally, pricing in farmers' markets in the study site is often in Rs5 increments) or from the experiment itself, which specified all payoffs at even Rs10 increments, its presence is clear.

[13] CE is defined by u(w+CE)=Eu(w+y) where w is non-stochastic wealth and y is a stochastic payoff. WTP is defined by u(w)=Eu(w+y-WTP). But as long as second order effects are relatively small, CE≈WTP.

$$WTP_{it} = \alpha_0 + \alpha_{EV} EV_t + \alpha_{SD} SD_t + \alpha_{Sk} Sk_t + \alpha_1 Play_{it} + \alpha_2 Earn_{it} + u_i + \varepsilon_{it}$$

where EV is expected value, SD is standard deviation, Sk is skewness (a dummy variable for T), u_i is a farmer random effect, and ε_{it} is an error term distributed $N(0,\sigma_\varepsilon^2)$. This specification directly tests farmers' valuation of the first three moments of the payoff distribution. The hypothesis that tests farmers' valuation of higher skewness is simply:

$H4_0$: $\alpha_{Sk}=0$ $\quad$ $H4_A$: $\alpha_{Sk}>0$ $\quad$ [higher skewness valuation]

As above, I estimate two additional moment effects models to capture farmers' incremental valuation of moments of the payoff distributions.

$$\Delta WTP_{it} = \alpha_0 + \alpha_{EV} EV_t + \alpha_{SD} SD_t + \alpha_{Sk} Sk_t + \alpha_1 Earn_{it} + u_i + \varepsilon_{it}$$
$$\Delta wtp_{it} = \alpha_0 + \alpha_{EV} EV_t + \alpha_{SD} SD_t + \alpha_{Sk} Sk_t + \alpha_1 Earn_{it} + u_i + \varepsilon_{it}$$

To identify the coefficients on the moment variables in these specifications, I must include the L distribution (because the B distribution is excluded in the estimation of these incremental specifications). To allow comparisons between these two specifications and the total WTP specification, I estimate the WTP model first excluding then including the L distribution.

Estimation results for these moment-effects models are shown in Table 3. On average, farmers value Rs1 of EV at Rs0.44, but value neither lower variance nor higher skewness. This result is confirmed for both total and incremental valuation and is robust to the inclusion of all farmers or only those who understood the experiment well.

Wealth and Risk Exposure Indices: The third set of models focus on farmer characteristics and require wealth and risk exposure indices, which I discuss and estimate in this subsection. The wealth index is the product of a vector of farmer wealth variables ($\mathbf{w}_i$) and a vector of corresponding weights ($\boldsymbol{\gamma}_\mathbf{W}$). The risk exposure index is analogously the product of a vector of farmer risk exposure variables ($\mathbf{r}_i$) and a vector of corresponding weights ($\boldsymbol{\gamma}_\mathbf{R}$). These scalar indices of farmer wealth and risk exposure are thus:

$$Wealth_i = \boldsymbol{\gamma}'_{\mathbf{W}} \mathbf{w}_{\mathbf{i}}$$
$$Risk_i = \boldsymbol{\gamma}'_{\mathbf{R}} \mathbf{r}_{\mathbf{i}}$$

To estimate $\boldsymbol{\gamma}_{\mathbf{W}}$ and $\boldsymbol{\gamma}_{\mathbf{R}}$, I use factor analysis so that the data determine the weights.[14] The results of this estimation approach are shown in Table 4.

The asset variables used in the wealth index include acres of non-irrigated land, Tropical Livestock Units (TLU, includes bullocks, cows and goats with weights 1, 1 and 0.1, respectively), television ownership, and ownership of a house with a concrete floor. Total expenses includes the total annual expenses (Rs) on clothes, education, electronics, and medicine and is meant to capture expenses that vary significantly across households according to wealth, rather than a complete accounting of household expenses. The coefficients and means shown in Table 4 suggest that total expenses and acres of non-irrigated land contribute the most to the average farmer's wealth index. Table 4 also shows hypotheses that test the existence of a common factor and whether more than one is needed.[15] Given the variables included in the wealth index, these tests suggest there is clearly a single common factor.

Wealth is generally a well-defined – if imperfectly measured – characteristic that researchers can reasonably hope to approximate with a scalar index. Capturing a farmer's or farm household's exposure to risk, on the other hand, poses an admittedly greater challenge. Others have computed related measures of vulnerability and risk exposure. Maxwell (1996) and Maxwell et al. (1999) construct a food insecurity index based on the frequency and severity of a household's responses to food shortages. Thus computed, the index captures the household's vulnerability to fluctuations in its food supplies. Mosely (2003), who also uses an experimental approach, constructs an index of

[14] I follow an iterative approach for selecting the variables included in $\mathbf{w_i}$ and $\mathbf{r_i}$. Beginning with a broad set of variables, I estimate an initial weight vector and compute a residual correlation matrix. When off-diagonal residual correlation is greater than 0.10 between two variables, I 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. See 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.

[15] These tests are possible because the coefficients were estimated using maximum likelihood.

'perceived vulnerability' based *inter alia* on an individual's memory and expectation of poverty to capture individual's attitude towards risk.

The risk exposure index I compute aims to capture exposure primarily to agricultural production risk. The index is based on the recent income and crop fluctuations experienced by farmers, their own perceptions about the riskiness of their income sources, and their ability to insulate themselves from drought through access to irrigation. The survey asked farmers to recall the worst farming season they had experienced in the last five years and to describe the causes and consequences of this particular season, including which crop was most severely affected. The first variable in the risk index indicates the percent of this crop that was lost in this particular season. The survey also asked farmers to list their three most important productive activities and how much of their total income came from each activity. The second and third variables, respectively, indicate the percent of a farmer's total income that comes from what he perceives to be 'very risky' and 'no risk' sources. The fourth variable is acres of irrigated land owned by the farmer.

The results in Table 4 suggest that the percent income from 'very risky' sources contributes the most to the average farmer's risk exposure index. Percent income from 'no risk' sources and total irrigated land reduce a farmer's risk exposure. Surprisingly, the percent crop lost in the worst season in five years also reduces a farmer's current risk exposure, suggesting either that the variable is measured with error or that farmers who were hard hit in a recent bad season have since altered their productive strategies to reduce their exposure. Hypothesis tests again confirm that there exists a single common factor.

The left panel of Figure 4 displays kernel density plots of the wealth and risk exposure indices.[16] The right panel of Figure 4 displays a scatter plot of the two indices with a kernel density

[16] Epanechnikov kernel with bandwidths of 0.18 and 0.17, respectively.

regression line of the wealth index on the risk exposure index.[17] These two indices are clearly uncorrelated (correlation coefficient -0.06).

Farmer Effects Models: With wealth and risk exposure indices in hand, I now discuss and estimate farmer effects models. These farmer effects model seek to understand differences between farmers in their valuation of seed traits. Do farmers with different characteristics value higher moments of yield distributions differently? This set of models seeks to shed some light on this question, which has important implications for the likely valuation and uptake of seeds – such as those considered to be 'pro-poor' – that confer primarily higher moment benefits. These models share the form:

$$WTP_{ijt} = f\left(\mathbf{m_t}, x_{1i}\mathbf{m_t}, \ldots, x_{Ni}\mathbf{m_t}, \mathbf{z_i}, \mathbf{g_{it}}, \mathbf{v_j}\right) + u_i + \varepsilon_{ijt}$$

where $\mathbf{m_t}$ is again a vector of the first three moments of payoff distributions (i.e., EV, standard deviation, skewness), $x_{1i},\ldots,x_{Ni}$ are scalar farmer characteristics so that $x_{ni}\mathbf{m_t}$ is a vector of farmer-moment interaction variables, $\mathbf{z_i}$ is a vector of (un-interacted) farmer characteristics, $\mathbf{g_{it}}$ is again a vector of game effect variables, $\mathbf{v_j}$ is a vector of village dummies, u_i is a farmer random effect, and ε_{it} is an error term distributed $N(0,\sigma_\varepsilon^2)$. Instead of fixed- or random-effects, farmer effects are now modeled explicitly using farmer-specific variables. Consider the following specification:

$$\begin{aligned} WTP_{ijt} = \beta_0 + \boldsymbol{\beta}^{\mathbf{t}\prime}\mathbf{m_t} + \boldsymbol{\beta}^{\mathbf{W}\prime} Wealth_i\mathbf{m_t} + \boldsymbol{\beta}^{\mathbf{R}\prime} Risk_i\mathbf{m_t} + \boldsymbol{\beta}^{\mathbf{Bt}\prime} Bt_i\mathbf{m_t} + \boldsymbol{\beta}^{\mathbf{M}\prime} MisUnd_i\mathbf{m_t} \\ + \beta_1 IrrL_i + \beta_2 Edu_i + \beta_3 Age_i + \beta_4 Play_{it} + \beta_5 Earn_{it} + \boldsymbol{\upsilon}'\mathbf{v_j} + u_i + \varepsilon_{it} \end{aligned}$$

where $Wealth_i$ is the wealth index for farmer i, $Risk_i$ is the risk exposure index,[18] Bt_i is a dummy variable that is 1 if farmer i has adopted *Bt* cotton and 0 otherwise, $MisUnd_i$ is 1 if farmer i understood the experiment with 'some confusion,' 'poorly' or 'very poorly' and 0 otherwise, $IrrL_i$ is

[17] Logistic kernel with bandwidth of 0.13.

[18] While the risk exposure index possibly introduces an endogeneity problem, there are no good instruments available for this index. This problem, which admittedly may bias the estimation results, arises because a farmer who chooses risky activities as his income sources may bid more for a risky payoff.

acres of irrigated land cultivated, Edu_i is years of education, Age_i is age in years, and all other variables are as defined above. Coefficient vectors (e.g., $\boldsymbol{\beta}^t=[\ \boldsymbol{\beta}_1{}^t\ \ \boldsymbol{\beta}_2{}^t\ \ \boldsymbol{\beta}_3{}^t\ \ \boldsymbol{\beta}_4{}^t\ ]$) are indicated in bold.

As before, I estimate two additional specifications of this model – ΔWTP and Δwtp – that focus on farmers' incremental valuation. I estimate both of these specifications with the L distribution included. Again, I estimate the WTP specification first excluding then including the L distribution to ensure comparability. Table 5 displays the estimation results for these three specifications. Consistent with the previous results, farmers appear to value only expected value and not lower variance or higher skewness. Wealthy farmers appear to value lower variance less than poor farmers. The magnitude of this wealth effect for H is even higher in the ΔWTP and Δwtp models. Wealth does not appear to affect farmers' valuation of skewness, which remains statistically zero.

The only risk exposure variable that is close to statistical significance at the 10% level is the skewness interaction variable (p-values are 0.13, 0.11, 0.26 for the WTP, ΔWTP, and Δwtp models, respectively).[19] Thus, there is weak evidence that farmers exposed to greater risks value a reduction in downside risk more than those exposed to less risk. The mean of the highest (lowest) quintile of the risk index is 0.76 (-0.79). Thus, the (Risk x Skew) coefficient in the ΔWTP model (p=0.11) implies a difference in the incremental valuation of the highest and lowest quintiles of about Rs4.5.

Bt cotton farmers appear to value lower variance slightly more than other farmers, although these effects are not strongly significant. Farmers who indicated they understood the experiment with 'some confusion,' 'poorly' or 'very poorly' seem to value EV substantially and significantly less than those who understood the experiment well. Note, however, that these misunderstand variables are meant to control for farmers' valuation, rather than explain it.

[19] Keep in mind, however, that the estimated risk exposure coefficients are potentially biased due to the possible endogeneity of the risk index.

Overall, these results suggest that, relative to wealthy farmers, poor farmers do not appear to value higher skewness of a distribution, but may value lower variance. The imprecision of the estimates, however, makes this evidence weak at best. Generally, while farmers are clearly not identical in their valuation of these experimental distributions, there are no clear patterns or strongly relevant farmer traits in the differences in their valuation. These results reinforce the conclusion from the treatment effects models that farmers are more responsive to changes in EV than in variance or skewness.

Limitations: In order properly to understand the analysis and results of this section, it is necessary to understand the limitations of the experiment used to elicit farmers' valuation of payoff distributions. The use of experimental economics in empirical development economics is nascent and will require further research in order to be fully understood and appreciated. This paper, including the design of the experiment and the data analysis, implicitly explores the use of experimental methodologies outside the laboratory and in development settings. This subsection briefly discusses some of the limitations of this methodology.

As mentioned previously, a major challenge in designing the experiment was striking an appropriate balance between context and abstractness. The lead enumerator would situate the experiment very clearly in a farming setting so that farmers better understood the experiment, but did not associate the changes in yield distributions with a particular seed trait. Keeping the payoff distribution abstract has a number of advantages. It also has some disadvantages. Would farmers have responded differently if it was explained that the truncated payoff distribution represented a seed that was perfectly protected from insects above some threshold pest load or from drought? It seems reasonable that specific downside threats such as pests and drought are feared by farmers. Framing the payoff distributions in terms of protection from pests or from drought may induce a higher WTP for a seed. It is also possible, though, that moving from abstract payoff distributions to the complexity of a farming context will cloud, not clarify, farmers' understanding of the advantages of a truncated distribution. Similarly, the experimental payoffs presume the farmer is cultivating a cash crop. While it is reasonable to posit that a subsistence farmer's risk preferences and his consequent valuation of different yield distributions would be markedly different, the farmers surveyed are more familiar with cash crops than purely subsistence crops.

Another possible limitation is that relatively wealthy farmers may not have treated the experiment as seriously as their poorer neighbors. A farmer's total expected payoff was intentionally designed to be higher than the daily wage rate for unskilled labor, a considerable amount for a poor farmer but less substantial for a wealthy one. Still, in experimental economic laboratories, even small payoffs can provide substantial incentives to participants (Davis and Holt 1993). Given the setting of the experiment, a more likely problem with wealthy farmers is that they may not be all that different from poor farmers. Even wealthy farmers are only wealthy relative to other farmers in their village and are in fact poor relative to wealthy farmers in other Indian states may help to explain why relative wealth does not significantly influence farmers' WTP.

A deeper limitation of an experimental methodology is that the researcher cannot ethically expose farmers to substantial risks of loss. For good reason, the experiment conducted in this project was designed so that farmers could lose a few Rupees in a particular round of the experiment, but their total net earnings were always positive. While this is an ethical necessity, it is also an important limitation to any study of downside risk preferences. Farmers' valuation of the higher moments of a payoff distribution would surely be more effectively elicited by an experiment that would subject farmers to gambles that include the risk of substantial loses. Of course, such experiments are ethically inappropriate. Generally, small short-term loses within an experiment are permissible so long as subjects' total net earnings are positive. But the risk of such loses may not simulate the larger livelihood risks that farmers in poor countries often face. On the other hand, subjects in experimental laboratories often display considerable loss aversion, which suggests that subjects still perceive these short-term loses as loses provided they are properly framed. It is therefore important to qualify the conclusions of this paper: Farmers may not value the higher moments of a payoff distribution when payoffs are small and mostly positive, but their valuation could change if instead they faced risks of substantial loses.

6 CONCLUSIONS

The analysis of this paper suggests that farmers are generally more responsive to changes in the expected value (EV) of a yield distribution than in the higher moments of the distribution. The farmers surveyed appear to value neither lower variance nor higher skewness even though both are presumably favorable for any risk-averse farmer. The key qualification to this finding is that, for good reason, the experiment used to elicit farmers' valuation did not subject them to the risk of substantial loses. Faced with more realistic, even life-threatening risks, farmers' valuation of these higher moments may be different. Still, the analysis seems relevant to the seed choices of farmers – the objective of the analysis – since these decisions are normally based on relatively small risk differences between seed varieties of a chosen crop.

There are some loose patterns in farmers' valuation. For example, wealthy farmers appear to value increases in EV, but poor farmers may value a decrease in variance more than the wealthy. Likewise, farmers who consider their sources of income to be quite risky value seem to value higher skewness in a payoff distribution, which implies lower downside risk, more than other farmers. But these findings are statistically weak and the results do not yield any strong conclusions about the effect of farmers' traits on their valuation of yield distribution properties. In short, most farmers – whether rich or poor, large or small – seem to value an increase in a mean payoff of a distribution, but appear indifferent about higher moments of the distribution.

There are several practical implications of these findings, especially related to the development and delivery of ‘pro-poor’ seeds with primarily higher moment benefits. If farmers do not value a lower variance or higher skewness in a crop yield distribution, then seed with a stabilized or truncated yield distribution must be marketed based on other traits. Not surprisingly, the best possible trait breeders could include to sell a seed would be a higher expected yield. In the many cases where this is difficult and unlikely, the practical benefits of a more stable yield with less downside risk (e.g., due to drought tolerance or pest resistance) could be highlighted to farmers. This seems to have been the case with *Bt* cotton in India, for example, where the pesticide savings associated with a higher skewness were central to the marketing of Bollguard™. These marketing considerations may be particularly important because the process of learning about the advantages of favorable higher moments of the yield distribution will likely be relatively slow. Additional research is required to understand how farmers think about yield stability and downside risk in order to inform the delivery and marketing of these seeds.

There are surely cases, however, in which neither breeding nor marketing are sufficiently effective. In such cases, farmers may only purchase such ‘pro-poor’ seeds if the price premium relative to benchmark varieties is low or even zero. For agro-services dealers, seed companies and plant breeders, this means that profit margins must be low, which brings up questions about financing the development and delivery of such seeds.

Lastly, while this paper has focused on farmers’ valuation of crop yield distributions, consumers also have a clear stake in yield distributions. For important food crops, a stabilized or truncated yield distribution could directly affect the distribution of food prices. If farmers protect themselves from catastrophic crop losses by purchasing risk-reducing seeds, consumers may benefit by seeing fewer price spikes at market. Thus, consumers may also value ‘pro-poor’ seeds and might willingly fund the development and delivery of such seeds, which could be promising for seeds with pure stabilizing traits that do not appear valued by farmers themselves.

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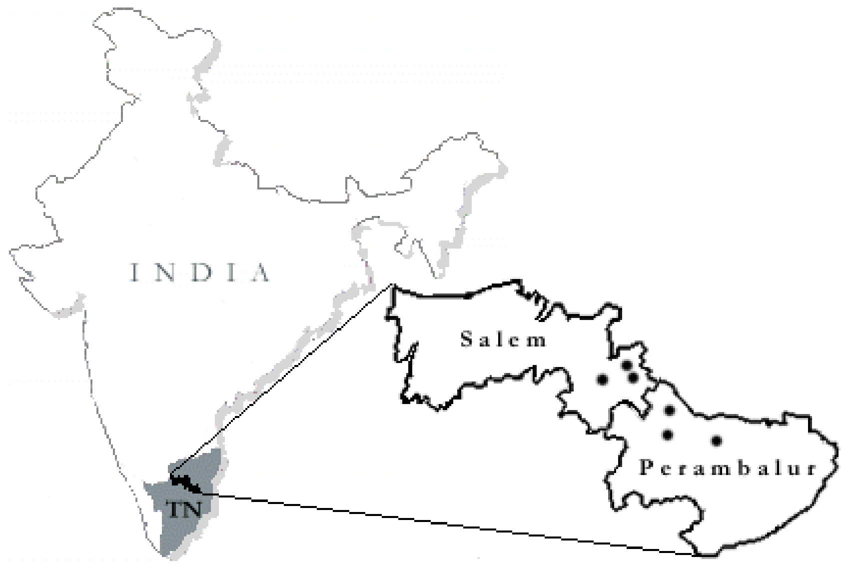

Figure 1 Map of surveyed villages in Salem and Perambalur districts of Tamil Nadu (TN), India (India map courtesy of www.theodora.com/maps, used with permission).

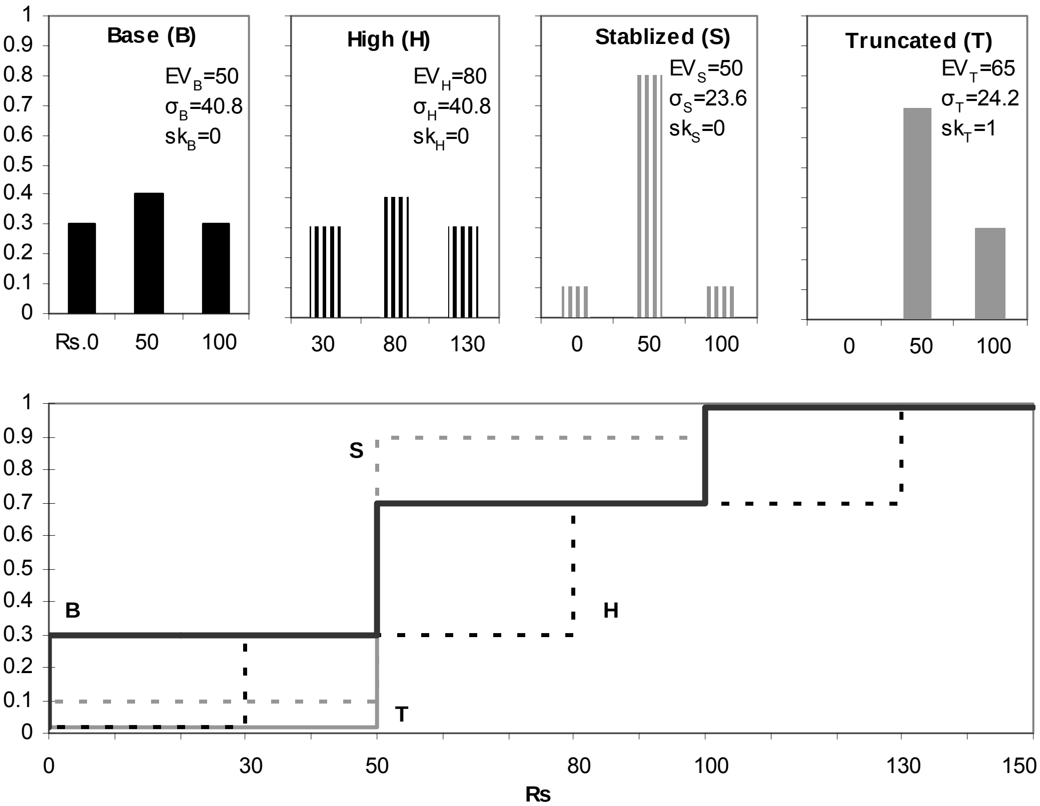

Figure 2 Marginal probability distributions (top) and cumulative probability distributions (bottom) for distribution types in experiment

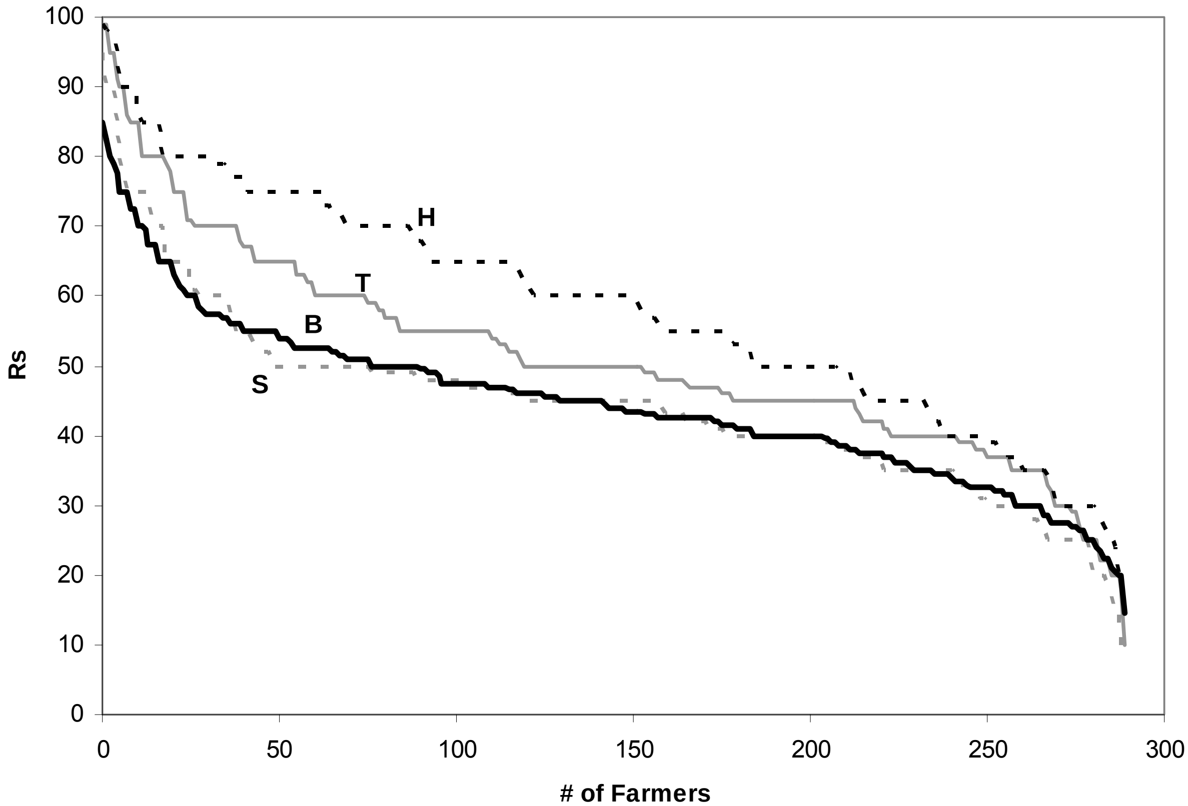

Figure 3 Demand curves for experimental distributions generated as graphs of ordered bid data.

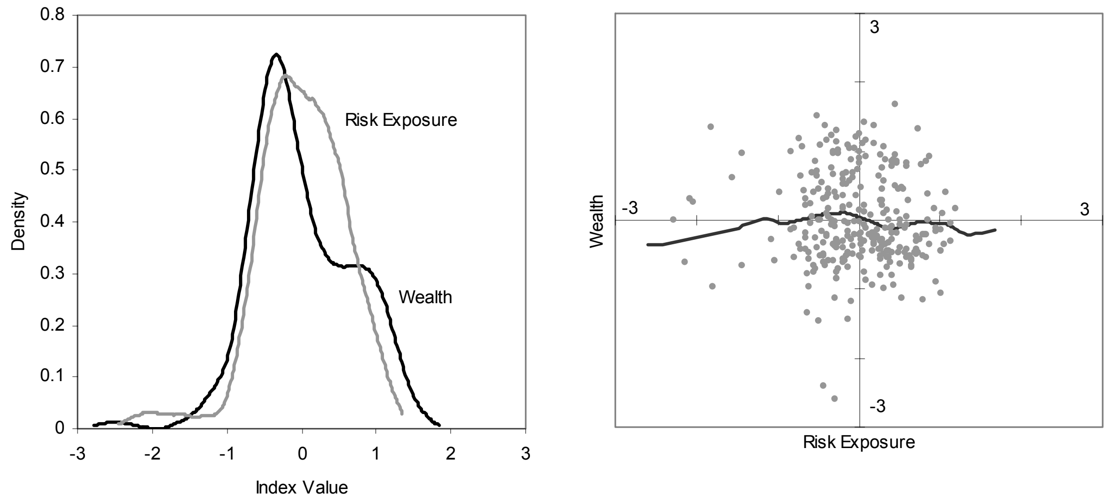

Figure 4 Non-parametric regressions of wealth index and risk exposure index densities (left) and scatter plot of wealth and risk exposure indices (right).

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 Estimation results for treatment effect models with farmer fixed-effects and standard errors corrected for between-farmer heteroscedasticity.

Model:	WTP (Rs)				ΔWTP over B (Rs)		Δwtp over B (%)	
			Risk Premium (RP)					
	Coeff.	Std.Err.	Rs	rp=RP/EV	Coeff.	Std.Err.	Coeff.	Std.Err.
	==== All Farmers ====							
Constant†	43.9 **	1.34	6	12%	-2.8 *	1.4	-2.1	3.7
Higher (H)	13.2 **	0.9	23	29%	13.4 **	0.9	31.4 **	2.5
Stabilized (S)	-0.40	0.85	7	13%				
Truncated (T)	6.3 **	0.84	15	23%	6.5 **	0.9	14.6 **	2.2
Previous Play {0,1}	-0.30	0.81						
Previous Earnings	0.02	0.01			0.04 *	0.02	0.10 *	0.04
Adj-R^2	0.34				0.40		0.38	
N=	1450				870		870	
	==== Farmers who understood experiment well ‡ ====							
Constant†	44.3 **	1.5	6	11%	-3.6 *	1.6	-2.3	3.8
Higher (H)	13.3 **	0.94	22	28%	14.0 **	1.0	33.3 **	2.5
Stabilized (S)	-1.0	0.94	7	13%				
Truncated (T)	6.4 **	0.93	14	22%	7.2 **	1.0	16.7 **	2.3
Previous Play {0,1}	-0.5	0.90						
Previous Earnings	0.02	0.02			0.042 *	0.018	0.094 *	0.045
Adj-R^2	0.33				0.42		0.42	
N=	1220				732		732	

†Constant is Base (B) in WTP and S in ΔWTP and Δwtp.

‡ Farmers who understood well are those indicating after the experiment that they understood the experiment 'well' or 'very well.'

* indicates significance at 10% level

** indicates significance at 1% level

Table 3 Estimation results for moment effects models with farmer random-effects.

Model:	WTP (Rs)		WTP (Rs)		ΔWTP (Rs)		Δwtp (%)	
L distribution:	Excluded		Included		Included		Included	
	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
	==== All Farmers ====							
Constant	22.6 **	2.5	21.2 **	2.3	-26.2 **	2.3	-56.0 **	5.8
EV	0.44 **	0.032	0.45 **	0.019	0.44 **	0.019	1.07 **	0.049
St.Dev	0.0170	0.055	-0.0020	0.050	-0.018	0.054	-0.072	0.14
Skewness	0.02	1.17	-0.32	1.10	-0.41	1.09	-1.82	2.78
Previous Play {0,1}	-1.9 *	0.86	-1.6 *	0.75				
Previous Earnings	0.012	0.015	0.027 *	0.013	0.067 *	0.017	0.13 *	0.042
N =	1450		1740		1160		1160	
	==== Farmers who understood experiment well ====							
Constant	21.5 **	2.8	20.0 **	2.6	-25.4 **	2.2	-52.1 **	5.4
EV	0.44 **	0.035	0.47 **	0.021	0.46 **	0.019	1.10 **	0.047
St.Dev	0.0510	0.061	0.0204	0.055	0.002	0.050	-0.142	0.12
Skewness	0.62	1.30	0.10	1.22	-0.28	1.10	-1.51	2.75
Previous Play {0,1}	-2.3 *	0.94	-2.2 **	0.83				
Previous Earnings	0.009	0.016	0.021	0.015	0.035 **	0.012	0.07 *	0.029
N =	1220		1474		976		976	

* indicates significance at 10% level

** indicates significance at 1% level

Table 4 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(Total 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.

Table 5 Estimation results for farmer-moment effects models with village fixed-effects and farmer random-effects.

Model:	WTP (Rs)		WTP (Rs)		ΔWTP (Rs)		Δwtp (%)	
L distribution:	Excluded		Included		Included		Included	
	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
Constant†	17.3 **	4.2	17.8 **	4.0	-34.5 **	4.2	-65.0 **	10.4
EV	0.49 **	0.045	0.46 **	0.026	0.45 **	0.026	1.1 **	0.067
St.Dev	0.034	0.079	0.053	0.071	0.073	0.077	0.094	0.20
Skewness	-0.88	1.7	-0.56	1.6	-0.72	1.6	-2.7	4.0
Wealth	-6.7 *	3.5	-4.6	3.3	-5.8 *	3.4	-12.8	8.6
Wealth x EV	0.092 *	0.049	0.028	0.028	0.026	0.027	0.070	0.070
Wealth x St.Dev	0.05	0.085	0.11	0.077	0.16 *	0.083	0.34 *	0.21
Wealth x Skew	0.0	1.8	1.0	1.7	1.0	1.7	2.9	4.3
Risk Exposure	-1.9	4.0	-3.2	3.8	-1.4	3.9	7.5	9.8
Risk x EV	-0.032	0.055	0.021	0.032	0.020	0.031	-0.018	0.080
Risk x St.Dev	0.065	0.096	0.019	0.087	-0.028	0.094	-0.25	0.24
Risk x Skew	3.61 *	2.0	2.87	1.9	3.0	1.9	5.5	4.9
Bt Cotton {0,1}	7.9 *	4.7	4.0	4.4	3.7	4.5	3.1	11.4
Bt Cotton x EV	-0.125 *	0.065	0.008	0.037	0.009	0.037	-0.010	0.094
Bt Cotton x St.Dev	0.034	0.11	-0.082	0.10	-0.20 *	0.111	-0.29	0.28
Bt Cotton x Skew	3.25	2.4	1.29	2.3	1.4	2.2	4.8	5.7
Misunderstand {0,1}	5.4	6.4	8.4	6.0	9.2	6.1	28.4 *	15.5
Misund x EV	0.01	0.1	-0.10 *	0.1	-0.10 *	0.050	-0.22 *	0.13
Misund x St.Dev	-0.20	0.2	-0.11	0.1	0.002	0.151	-0.20	0.38
Misund x Skew	-3.82	3.3	-2.21	3.1	-2.1	3.0	-8.7	7.7
Ln(Irr.Land)	-0.14	0.77	-0.32	0.74	0.02	0.84	-1.4	2.0
Education	-0.05	0.14	-0.05	0.13	-0.09	0.15	-0.32	0.36
Age	0.02	0.05	0.01	0.05	0.13	0.06	0.13	0.13
Previous Play {0,1}	-1.8 *	0.87	-1.5 *	0.76				
Previous Earn	0.01	0.01	0.03 *	0.01	0.07	0.02	0.14	0.04
N=	1450		1740		1160		1160	

†Village fixed-effects results are suppressed.

* indicates significance at 10% level

** indicates significance at 1% level