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Farmer Preferences for Drought Tolerance in Hybrid versus Inbred Rice

Evidence from Bihar, India

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ABSTRACT

Recent efforts to develop rice cultivars with drought-tolerance (DT) traits have resulted in the release of several varieties that demonstrate significant resilience to drought stresses. This paper addresses the previously unanswered question of whether the private sector might play a future role in developing similar strains through applications of advanced biotechnology, and whether their research and development efforts would benefit poor and vulnerable farmers in hazard-prone ecosystems. We employ discrete choice experiments to examine farmers' preferences for DT traits and explore heterogeneity in these preferences using primary data collected in rural Bihar, India. Using different modeling approaches to capture preference heterogeneity, our results show that farmers value the reduction in yield variability offered by DT cultivars but are willing to pay even more for rice seed that offers yield advantages even under normal conditions. We demonstrate that risk aversion and loss aversion are important components of farmer utility, as these behavioral parameters not only significantly influence choice probabilities but also affect the way farmers value different seed attributes.

Keywords: choice experiments, drought tolerance, risk, rice, India

JEL Codes: Q12, Q16, O33

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1. INTRODUCTION

Droughts represent a significant constraint to rice production in much of India. Roughly 20 percent of India's total land area is drought prone, including 16 million hectares (ha) of rainfed lowland rice and 6.3 million ha of upland rice. When droughts occur, there are significant negative impacts on rice production, both in reductions in area cultivated and in lower yields, resulting in lower rice production and lower farm incomes. In addition to these immediate, farm-level consequences, there are often significant secondary household impacts such as indebtedness, asset depletion, and health consequences that perpetuate already high levels of poverty and deprivation in India (World Bank 2008). Even broader and economywide impacts include rapid increases in rice prices that can increase vulnerability among food-insecure households and strains of fiscal expenditures required to offset price increases and operate social protection schemes. This situation is disconcerting since evidence suggests that droughts have been occurring with greater frequency in India since the beginning of the twentieth century (World Bank 2008).

Recent efforts to develop rice cultivars with drought-tolerance (DT) traits have resulted in the release of several varieties that demonstrate significant resiliency to drought stresses with no yield penalty under normal conditions.[1] Simulation exercises aimed at assessing the impacts of DT rice suggest that the successful development and delivery of these varieties will produce significant benefits across south Asia, well in excess of the investments necessary to develop the technology (Mottaleb et al. 2012). Although this holds potential promise for both public- and private-sector research efforts, Lybbert and Bell (2010) argue that development of DT cultivars does not necessarily imply that DT varieties will be widely adopted with the same speed as other recent improvements (for example, crops genetically engineered to contain the *Bacillus thuringiensis* toxin, thereby making crops virtually impervious to insect infestation) due primarily to the nonmonotonic nature of the benefits associated with drought tolerance and their effect on social learning and technology diffusion.

In this paper, we use discrete choice experiments to examine farmers' preferences for DT traits embodied in different rice backgrounds (hybrid and varietal) and explore heterogeneity in these preferences. This distinction is motivated by differences in the potential avenues or scenarios through which such traits could be embodied in seed technologies.

In the scenario that characterizes most of India's innovation in rice to date, public research institutions (for example, Indian state agricultural universities or institutes of the Indian Council of Agricultural Research) develop inbred cultivars with desirable traits such as higher yield, shorter duration, or drought tolerance. These inbreds are then distributed through various channels as low-cost seeds that small-scale, resource-poor farmers can save and replant each season. In an alternative scenario that is much less common in rice, it is the private, profit-maximizing firm (for example, crop-science company or seed company) that develops these desirable traits, typically by introducing them in a hybrid, rather than inbred, background that allows the firm to maintain control over the gains afforded by its innovation. We examine this in greater detail below and simply highlight here the idea that multiple scenarios may play out in the development of drought-tolerant rice, each with implications for the potential impacts on poverty and productivity in countries such as India.

The remainder of this paper is organized as follows. In Section 2, we provide background about rice production in India, paying specific attention to the challenges wrought by frequent droughts in key rice-growing regions. In Section 3, we describe the empirical methodology used in analyzing farmer preferences and demand heterogeneity. In Section 4, we describe the data used in this study, including the geographic and socioeconomic context of our sample area. In Section 5, we present the results of our empirical analysis. Finally, we offer some concluding remarks in Section 6.

[1] Recent research has involved improvements in terms of both drought tolerance and drought resistance. Although the terms are often used interchangeably, they in fact describe different physiological phenomena. Drought tolerance involves enduring periods with scanty or deficient water supplies. Drought resistance, on the other hand, generally involves mechanisms by which plants protect themselves from the harsh drying sun during drought conditions. Throughout the remainder of this paper, we will use the term drought tolerant as a generic term describing crops that are both drought tolerant and drought resistant.

2. BACKGROUND ABOUT RICE PRODUCTION IN INDIA AND THE CHALLENGES ASSOCIATED WITH DROUGHTS

During the Green Revolution, the introduction of modern agricultural inputs such as improved seeds, fertilizers, and pesticides—along with supportive policies and investments in credit, pricing, research, and infrastructure—greatly increased agricultural production in India (see, for example, Hazell 2010). However, the Green Revolution's impacts in India were largely confined to the country's main irrigated areas and favorable agroecologies, most notably the western Indo-Gangetic plains (Punjab, Haryana, and western Uttar Pradesh) where irrigation infrastructure was most developed and where the provision of credit and fertilizers was particularly concentrated (Evenson and Gollin 2003; Kumar et al. 2008).

In other parts of India, including the eastern reaches of the Indo-Gangetic plains (including eastern Uttar Pradesh, Bihar, and West Bengal) where irrigation was slow to develop, the innovations associated with the Green Revolution are still being introduced today. Even despite such investments, the rate of yield growth for rice across India has decelerated in recent decades alongside a similar deceleration in wheat yields. Although some estimates of food supply do not suggest an impending Malthusian crisis (for example, Ganesh-Kumar et al. 2012), there is still a need for increased investment in new and innovative technologies that improve yield, conserve scarce natural resources used in production, and resist both biotic and abiotic stresses associated with changing climate patterns.

Droughts represent one of the most pressing constraints to rice yields in unfavorable and rainfed ecosystems (Pandey, Bhandari, and Hardy 2007; Serraj et al. 2009). Since the early 1960s, there have been 15 instances in which total rice production in India failed to exceed the production level from the previous year. Not coincidentally, the majority of these have coincided with significant droughts in key rice-growing regions. The dynamics of drought impacts involve a complex interaction between climate, weather, infrastructure, and human behavior. The ultimate agricultural and societal impacts of droughts are dependent on factors such as the timing and severity of the drought. For example, the 2002 drought was particularly destructive to rice production, affecting some 300 million people across India, some in the most important rice-producing states in India such as Uttar Pradesh, Andhra Pradesh, Punjab, Orissa (now Odisha), and Tamil Nadu. For the country as a whole the monsoon season rainfall was roughly 20 percent below the historical average, mainly due to a significant dry spell in July, during which rainfall was 49 percent below the long-run average, the largest monthly rainfall deficiency in recorded history (IMD 2002).

Questions remain as to whether existing technologies—combined with improved crop management practices—can meet the demands of growing populations under these increased stresses. The development of DT traits for a variety of crops has been seen as a potential avenue through which human livelihoods can be at least partially insulated from the effects of droughts. However, drought resistance has, until recently, received relatively little attention from plant breeders.[2] Despite significant challenges and early setbacks, research on drought tolerance is proceeding in both the public and the private sectors and at both global and national levels. Many agricultural scientists and development practitioners agree that DT varieties present a means of avoiding the increasing threat of droughts. An ex ante assessment by Mottaleb et al. (2012) suggests that the development of such rice varieties would provide significant benefits in both economic benefits to farmers and nutritional benefits to consumers, concluding that the monetized benefits of these advances exceed the costs of research and development necessary to bring these varieties to market.

[2] For an early example of the failure to marshal resources around research on drought resistance, see Doering (2005).

This is not to say that the dissemination and adoption of DT rice varieties, once developed, will be rapid or straightforward processes. Lybbert and Bell (2010) argue that the nature of drought—and crop responses to drought—make adoption pathways for DT varieties more complicated than those for varieties tolerant to other stresses, particularly insect-resistant crops.[3] Among other important differences, they argue that drought tolerance introduces nonmonotonic benefits relative to nontolerant varieties, which as a productivity-enhancing (yield-variability-reducing) benefit rather than purely a productivity-increasing (yield-increasing) benefit, introduces stochastic-relative benefit streams that may complicate the decisionmaking calculus of risk-averse farmers.[4] But the benefits of DT rice may be nearly monotonic, as currently available DT rice varieties provide farmers with significant yield advantages over conventional varieties even under severe drought conditions. Thus, Lybbert and Bell (2010) should perhaps be interpreted as providing a caveat that interventions may be needed to expedite the widespread adoption of DT crops.

Although current efforts in developing DT technologies have resulted in self-pollinating (inbred) DT varieties, this study also considers the possibility that DT traits could be embodied in a hybrid background as an alternative solution. The relative yield advantage of hybrids under irrigated systems is well documented, with some studies estimating hybrids yielding 10–30 percent higher than varieties in India, China, and Bangladesh (see, for example, Li, Xin, and Yuan 2010; Lin 1991; Virmani, Aquino, and Khush 1982; Virmani 2003; Janaiah and Hossain 2003). Developing hybrids with both high yield potential and DT traits could both improve and stabilize yields in drought-prone environments (Villa et al. 2012).

In addition to higher yield potential, hybrids offer economic incentives to private innovators. The economic value of hybrids stems from yield gains and other benefits conferred by *heterosis* (hybrid vigor) declining dramatically after the F1 generation, thus compelling farmers to purchase new F1 seed each season if they want to continually realize these benefits. These purchases of F1 seed provide innovators—breeders and seed companies—with a means of recouping their investments in research and the high fixed costs of producing hybrids (for example, seed multiplication). Where innovators can produce and market hybrids with desirable traits while also maintaining secrecy about the hybrid's pedigree as a biological form of intellectual property protection, they are often able to operate at a profitable margin even in seed markets where farmers are relatively poor. This has been demonstrated with hybrid maize in Latin America and southern and eastern Africa (see Smale and Jayne 2010; Morris 1998) and with hybrid rice in China (Li, Xin, and Yuan 2010). This has also been demonstrated with insect-resistant (*Bt*) hybrid cotton in India, where hybrids have served as the platform for private investment in the introduction of genetically modified traits (Kathage and Qaim 2012; Gruere and Sun 2012). Analogous development of hybrid DT rice by the private sector is part of the motivation underlying this study.

Although hybrid rice in India is still characterized by low rates of adoption (on the order of 6 percent nationally), and although hybrid rice is still fraught with issues such as poor cooking qualities and variable yield performance, there is a sense that hybrid rice will play an important role in the future of rice production in India, particularly via private crop-science and seed companies. The government of India has set its sights on introducing hybrid rice on 25 percent of all cultivated rice area by 2015. Although this may not be feasible, there are indications of high adoption levels in poorer northeastern states such as Bihar—the area of focus in this study—where 24 percent of farmers had cultivated hybrid rice at least once as of 2009 (Spielman, Kolady, and Ward 2013).

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[3] The genetically modified insect-resistant crops referred to here share a similar insect-resistance trait that is conferred by the introduction of genes from the soil bacterium *Bacillus thuringiensis* (Bt) into their DNA. Although Bt cotton and Bt maize are the largest commercial applications of this technology, Bt has also been introduced into potato, soybeans, and *brinjal* (eggplant), among other crops.

[4] We define a productivity-enhancing benefit as one that either increases yield or reduces yield variability or yield susceptibility to stress, whereas a productivity-increasing benefit more narrowly only increases yield. In this regard, productivity-enhancing technologies involve higher-order moments of the yield distribution, whereas productivity-increasing technologies involve only the first-order moment.

3. EMPIRICAL METHODOLOGY

Our empirical methodology is based on using experimental choice modeling methods to analyze farmers' preferences for seeds among a series of alternatives. Choice modeling has become an increasingly important mode of studying economic behavior and demand patterns since this methodology allows the researcher to estimate marginal values for various attributes embodied in different goods or services, including nonmarket goods and services for which such marginal valuations are difficult or impossible to measure by examining revealed preferences. In addition, choice modeling allows for relatively straightforward estimation of welfare effects arising from incremental changes in the levels of the attributes included in the analysis (Colombo, Hanley, and Louviere 2009). Within the agricultural and environmental economics literature, choice experiments have been used extensively for analyzing consumer preferences for environmental amenities (for example, Adamowicz, Louviere, and Williams 1994; Boxall et al. 1996; Bennet and Blamey 2001), analyzing food certification and food safety attributes (for example, Lusk, Roosen, and Fox 2003; Nilsson, Foster, and Lusk 2006; Lusk, Norwood, and Pruitt 2006; Loureiro and Umberger 2007; Ubilava and Foster 2009; Ortega et al. 2011), analyzing adoption of voluntary traceability systems in cow-calf operations (Schulz and Tonsor 2010), and quantifying welfare effects of various agricultural and food policies (Ortega et al. 2012; Lusk and Briggeman 2009; Tonsor, Olynk, and Wolf 2009).

In the context of this study, the use of choice experiments allows us to elicit farmers' willingness-to-pay (WTP) for DT as a characteristic embodied in rice. Choice experiments represent an empirical application and extension of the theoretical and conceptual work of Lancaster (1966). It may at first seem inappropriate to use an empirical approach designed within the context of consumer theory to understand producer behavior. In fact, such an approach has rarely been attempted with technology adoption, even though agricultural technologies (especially biotechnologies) are often differentiated largely on a trait-by-trait basis (Useche, Barham, and Foltz 2009). In situations in which there are missing markets or in which the traits of a particular technology exhibit nonmonetary effects or otherwise give rise to nonseparability, the production and consumption decisions of the household must be taken simultaneously. Under these conditions, it is appropriate to view technology-adoption decisions as components of a utility-maximization problem, wherein utility of farm profits is maximized by choosing a combination of technology attributes among a set of feasible alternatives (for example, Useche, Barham, and Foltz 2012). By incorporating technology choices, farm production, and farm profits in a utilitarian framework, we are able to analyze the demand for and welfare implications of traits that affect the variability of expected profits.

Choice experiments closely simulate real-world purchasing decisions. In these experimental settings, consumers are asked to choose among a series of alternative bundles of attributes. Suppose that individual i faces K alternatives contained in choice set $\mathcal{S}$ during occasion t We can define an underlying latent variable V_{ijt}^* that denotes the value function associated with individual i choosing option $j \in \mathcal{S}$ during occasion t. For a fixed-budget constraint, individual i will choose alternative j so long as $V_{ijt}^* >. V_{ikt}^* \; \forall k \neq j$. The researcher does not directly observe V_{ijt}^*, but instead directly observes V_{ijt},, where

$$V_{ijt} = \begin{cases} 1 & \text{if } V_{ijt}^* = \max(V_{i1t}^*, V_{i2t}^*, \dots, V_{iKt}^*) \\ 0 & \text{Otherwise} \end{cases} \tag{1}$$

Following standard practice, we assume that indirect utility is linear, which ensures that marginal utility is strictly monotonic in traits and yields corner solutions in which only one good is purchased (Useche, Barham, and Foltz 2012). We can write individual i's utility function as

$$V_{ijt}^* = X_{ijt}'\beta + \varepsilon_{ijt} \tag{2}$$

where X'_{ijt} is a vector of attributes for the j^{th} alternative, β is a vector of taste parameters (that is, a vector of weights mapping attribute levels into utility), and ε_{ijt} is a stochastic component of utility that is independently and identically distributed across individuals and alternative choices and takes a known distribution. This stochastic component of utility captures unobserved (to the econometrician) variations in tastes and errors in consumers' perceptions and optimization.

The probability of observing $V_{ijt} = 1$ (that is, the consumer chooses option j given all other alternatives in $\mathcal{S}$) can be written as

$$\text{Prob}(V_{ijt} = 1) = \text{Prob}\left(X'_{ijt}\beta + \varepsilon_{ijt} > X'_{ikt}\beta + \varepsilon_{ikt}\right)\ \forall k \in \mathcal{S}, \forall k \neq j \tag{3}$$

We assume that the random component of utility ε_{ijt} follows a Gumbel (extreme value type I) distribution with cumulative distribution function $F(\varepsilon_{ijt}) = \exp\left[-\exp\left(-\varepsilon_{ijt}\right)\right]$and corresponding probability density function $f(\varepsilon_{ijt}) = \exp[-\varepsilon_{ijt} - \exp(-\varepsilon_{ijt})]$. Rearranging terms in equation (3), we can easily observe that

$$\text{Prob}(V_{ijt} = 1) = \text{Prob}\left(\varepsilon_{ikt} < X'_{ijt}\beta + \varepsilon_{ijt} - X'_{ikt}\beta\right)\ \forall k \in \mathcal{S}, \forall k \neq j \tag{4}$$

Then, under the assumption that $\varepsilon_{i1t}, \varepsilon_{i2t}, \dots, \varepsilon_{iKt}j$ are identically and independently distributed, we can write our expression for the probability of observing alternative *j* chosen over all other alternatives conditional on the observed levels of the attribute vector for all alternatives in the choice set $\mathcal{S}$ as

$$\text{Prob}\left(V_{ijt} = 1 | X'_{i1t}, X'_{i2t}, \dots, X'_{iKt}, \beta\right) = \frac{\exp\left[X'_{ijt}\beta\right]}{\sum_{k=1}^{K} \exp[X'_{ikt}\beta]} \tag{5}$$

which is the basic multinomial logit model and can be estimated using maximum likelihood.

Given the utilitarian interpretation of our econometric specification, the N −vector of parameters $\beta = (\beta_1, \beta_2, \dots, \beta_N)$ defining tastes and preferences over the Nattributes can be interpreted as marginal utilities, and the ratio of two such marginal utilities is simply the marginal rate of substitution of one for the other. If one of the included attributes (say, the N^{th} attribute) is the price of the alternative, then N can be interpreted as the marginal utility of price (or cost). With an estimate for the marginal utility of money, the marginal rate of substitution of money for each of the corresponding attributes—that is, WTP—can be estimated as

$$\text{WTP}_n = -\frac{\beta_n}{\beta_N}, n \in [1, N-1] \tag{6}$$

where β_n is the estimated parameter for the n^{th} attribute. The negative sign appears because the marginal utility of cost is assumed to be negative, whereas the marginal utility for favorable (unfavorable) attributes will be positive (negative); thus, we must take the negative of this ratio to ensure that WTP for a favorable (unfavorable) attribute is represented as a positive (negative) value.

Because farmers are heterogeneous, their preferences for drought tolerance may also be heterogeneous. Within the discrete choice literature, there are several ways to account for preference heterogeneity. A common method of evaluating preference heterogeneity is estimation of random parameters logit models, also called mixed logit. The random parameters logit is regarded as a highly flexible model that can approximate any random utility model and relaxes the limitations of the traditional multinomial logit by allowing random taste variation within a sample according to a specified distribution (McFadden and Train 2000). Following Train (2003), the probability that individual i chooses alternative j from the choice set $\mathcal{S}$ in situation t is given by

$$\text{Prob}\left(V_{ijt} = 1 | X'_{i1t}, X'_{i2t}, \ldots, X'_{iKt}, \Omega\right) = \int \frac{\exp\left(X'_{ijt}\beta_i\right)}{\sum_{k=1}^{K}\exp\left(X'_{ikt}\beta_i\right)} f(\beta|\Omega)d\beta \tag{7}$$

where the vector Ω defines the parameters characterizing the distribution of the random parameters, which the researcher can specify. For our purposes, we allow the coefficients corresponding to all attributes except price to vary normally. We restrict price to be constant, effectively ensuring a negative marginal utility of price and facilitating easier computations of WTP.

Alternatively, we can introduce heterogeneous preferences by segregating farmers into groups with similar underlying characteristics. This approach, known as latent class modeling, assumes that $f(\beta)$is discrete, taking C distinct values (Train 2003). The probability that farmer i selects option j in a given choice situation t unconditional on the class is represented by

$$\text{Prob}\left(V_{ijt} = 1 | X'_{i1t}, X'_{i2t}, \ldots, X'_{iKt}, \beta\right) = \sum_{c=1}^{C} \frac{\exp\left(X'_{ijt}\beta_c\right)}{\sum_{k=1}^{K}\exp\left(X'_{ikt}\beta_c\right)} Q_{ic} \tag{8}$$

where β_c is the class-specific taste parameter vector for class c and Q_{ic} is the probability that farmer i falls into class c:

$$\text{Prob}(class_i = c) = Q_{ic} = \frac{\exp(Z'_i\theta_c)}{\sum_{c=1}^{C}\exp(Z'_i\theta_c)}, \quad \theta_C = 0 \tag{9}$$

This probability can be random (that is, $Z_i = 1\ \forall i$) or conditioned by a vector of household characteristics (that is, $Z'_i = [1, z_{i1}, z_{i2}, \ldots, z_{iM}]'$) and corresponding coefficient vector corresponding to membership in class c. Combining these two equations, we can write

$$\text{Prob}\left(V_{ijt} = 1 | X'_{i1t}, X'_{i2t}, \ldots, X'_{iKt}, Z_i, \beta, \theta\right) = \sum_{c=1}^{C} \left[\frac{\exp\left(X'_{ijt}\beta_c\right)}{\sum_{k=1}^{K}\exp\left(X'_{ikt}\beta_c\right)}\right]\left[\frac{\exp(Z'_i\theta_c)}{\sum_{c=1}^{C}\exp(Z'_i\theta_c)}\right] \tag{10}$$

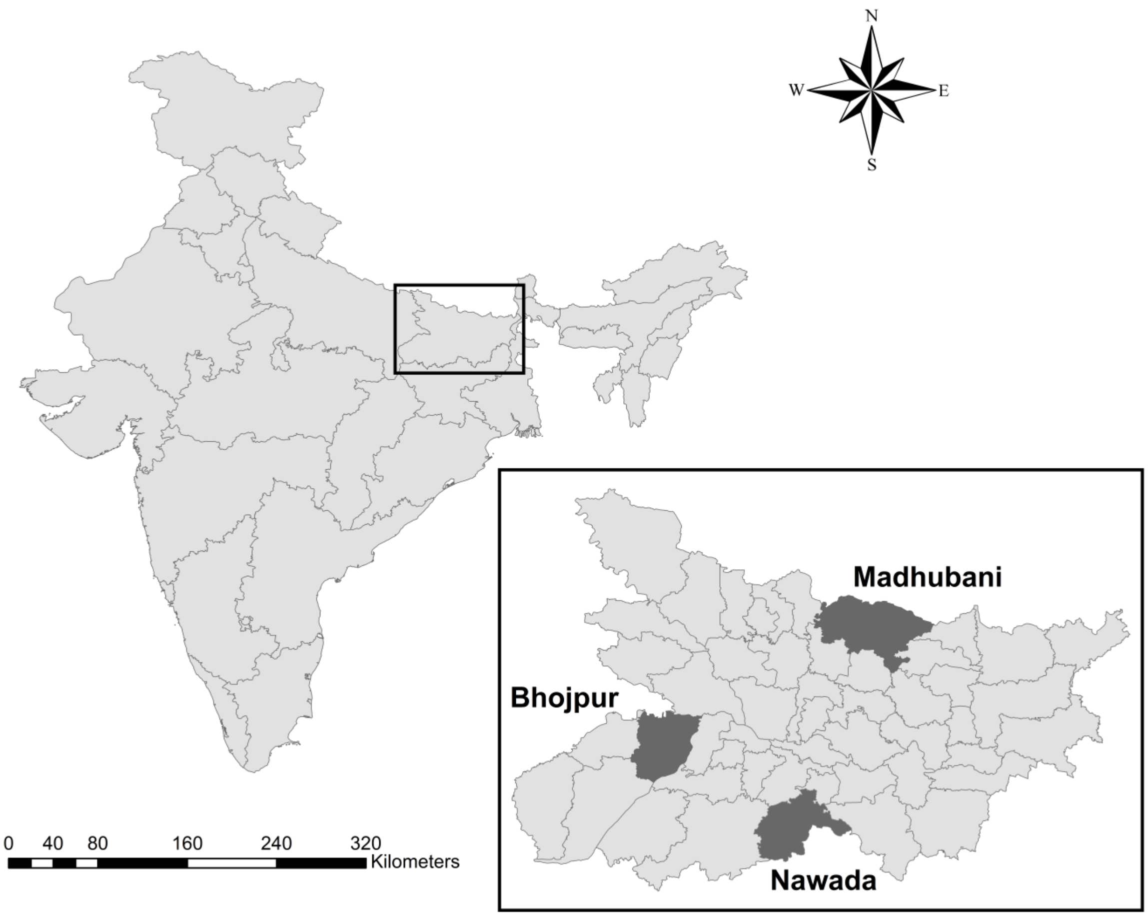
In addition to being conditioned on the attributes of the various alternatives included in the choice task in period t and the specification of Z'_i, this defines the probability of a particular alternative's being selected in a given choice set as a function of membership in a particular class as well as the class-specific vector of parameters mapping attribute levels into utility. This specification therefore allows for homogeneous preferences within a series of heterogeneous classes of farmers.[5]

[5] This specification could be modified to incorporate random parameters, thus introducing individual heterogeneity within the heterogeneous classes. This was attempted in the current study, but it was found that the estimated taste parameters within each class exhibited no statistically significant variation, implying that almost all of the heterogeneity could be accounted for by latent class segmentation.

4. DATA

The data used in this study are derived from household surveys conducted in the state of Bihar, India (Figure 4.1). Although roughly 90 percent of the state's population live in rural areas (compared with only 72 percent at the national level), Bihar has the highest population density of any state in India, with an estimated 1,104 persons per square kilometer as of 2011.[6] Bihar also has the lowest statewise per capita income in India, at only 35 percent of the national average in 2009–10 (Government of Bihar 2012).

Figure 4.1 Location of sample districts



Source: Authors.

Because of topographical and climatic conditions, Bihar is vulnerable to meteorological and hydrological hazards on a recurring basis, particularly flood and droughts. Nearly 50 percent of the total cultivated area in Bihar is prone to these hazards. Bihar's vulnerability to droughts has become much more apparent and urgent in recent years. Though roughly 57 percent of gross rice cropped area is irrigated (in some fashion or another), a large share of this irrigation infrastructure relies on diesel-powered pumps, which significantly increase farmers' production costs, especially during years when rainfall is scarce or when monsoon rains are delayed. It seems plausible that the development and delivery

[6] This ranking excludes union territories such as Chandigarh and Delhi, which each have more than 9,000 persons per square kilometer.

of rice varieties and hybrids that demonstrate resiliency to drought conditions could significantly reduce output variability and reduce farmers' vulnerability to these hazards.

Our sample consists of 475 rice-producing households in rural Bihar. We used a multistage sampling approach to form our survey sample. In the first stage, we selected three districts heavily dependent on rice production in which to sample households: Bhojpur, Madhubani, and Nawada. These three districts provide a great deal of heterogeneity, not least in geography and agroecology. Madhubani and Nawada are both participants in the government of India's Drought-Prone Area Programme as of 2010, whereas Bhojpur and Nawada were participants in the Drought-Prone Area Programme from 2002 to 2010. All three districts were affected by rainfall deficiencies during *kharif* 2012: Nawada and Madhubani had rainfall deficiencies of 49 percent and 48 percent, respectively, and Bhojpur had a rainfall deficiency of 32 percent (IMD 2012).[7] In the second stage, we selected 16 high-rice-producing blocks across the three districts. The number of blocks drawn from each district is proportional to the share of rice production attributable to each district.[8] We selected 7 blocks from Bhojpur, 3 from Nawada, and 6 from Madhubani. Within each of these blocks, we randomly selected two villages from which to draw households. From these villages, we randomly selected 18 rice-growing households from village rosters prepared by enumerators through door-to-door listing. After eliminating households for which data are missing, our sample consists of 226 households from Bhojpur, 146 households from Madhubani, and 103 households from Nawada.

For the choice experiment, the alternatives that the individuals were presented were comprised of varying levels of key attributes that are thought to be the most important characteristics that condition seed-purchasing decisions. The attributes included in our choice experiment and the levels over which they vary were determined through consultation with scientific experts, focus group discussions with farmers, pretesting choice experiments in the field, and careful review of the related literature.

Paddy yield has been widely identified as the most important attribute that farmers consider when deciding on which rice to cultivate. Since yields are ultimately the result of both deterministic and stochastic processes, it is possible that farmers consider yields under both normal and drought stress conditions to be important. A study by Dalton, Yesuf, and Muhammad (2011) that explores farmers' demand for DT maize in Kenya characterized drought tolerance by quantifying yields under different rainfall scenarios, corresponding to maize varieties with different forms of stochastic dominance relative to a popular local variety: one in which the improved variety first-order stochastically dominated (FSD) the reference variety, one in which the improved variety second-order stochastically dominated (SSD) the reference variety, and a final distribution in which the improved variety third-order stochastically dominated (TSD) the reference variety.[9] Such an approach involves an attribute (DT) with three distinctly varying levels (FSD, SSD, and TSD), though each attribute level is presented as yields under three different rainfall conditions. In other words, farmers aren't required to think about stochastic dominance but only about potential yields under different conditions, simplifying the choice task for the respondent. This offers a novel method for characterizing dehydration tolerance (that is, in contrast to drought escape through a shorter duration to maturity) without necessarily specifying the pathway by which such tolerance was achieved.

We have used a similar approach to quantifying drought tolerance in the present study. Our yields under different stress conditions are derived based on both published figures for a newly released DT variety and hypothetical yields that may be obtained through hybridization. Researchers from the

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[7] The *kharif* season is the monsoon season in India, which lasts from roughly mid-June through the end of September.

[8] These figures are based on average total rice production during 2007–2008, 2008–2009, and 2009–2010. On average, total rice production was 227,733 metric tons (42 percent) in Bhojpur, 118,163 metric tons (22 percent) in Nawada, and 196,621 metric tons (36 percent) in Madhubani.

[9] Specifically, the FSD variety had higher yields than the check variety (IR 64) under normal conditions (thereby providing a higher expected yield) as well as under both moderate and severe drought stress conditions (thereby providing lower yield variability). The SSD variety yielded the same as the popular local variety under normal conditions (thus preserving mean or expected yields) but yielded higher under both moderate and severe drought stress. The TSD variety yielded the same as the popular local variety under both normal and moderate stress conditions but yielded higher under severe drought stress conditions (thereby providing protection against extreme downside risk).

International Rice Research Institute (IRRI) have been actively engaged in research on DT rice and have released a DT rice variety (Sahbhagi dhan) for use in Jharkhand and Odisha, which will soon be tested in Bihar. This variety has been shown to give better yields over check varieties in trials conducted during the 2005–2007 *kharif* seasons, under both stressed and nonstressed conditions. Under severe drought conditions, Sahbhagi dhan provided a 1 ton per hectare yield advantage over IR 64 and IR 36, two prominent megavarieties grown throughout eastern India. The yield distribution of Sahbhagi dhan under various water stress conditions has provided important guidance in specifying the yield distributions for potential varieties presented in our choice experiment.

For hypothetical DT hybrids, we had to consider the yield advantages presented by heterosis and consider how such yield advantages might decay with increased drought stress. Based on personal communication with rice breeders from IRRI, it was determined that depending on the parental lines used in the hybridization process, a feasible scenario for a DT hybrid is that it would yield 15 percent higher than Sahbhagi dhan under normal conditions but that this yield advantage would diminish to 10 percent under moderate drought stress conditions and 5 percent under severe drought stress conditions (Arvind Kumar, personal communication).[10] We are therefore able to specify yield distributions that roughly correspond with inbred varieties and hybrids with differing degrees of stochastic dominance relative to local check varieties. In the actual choice sets, we do not identify the seeds as either inbred or hybrid but merely allow for the attribute to have six levels. A summary of these yield attribute levels is seen in Table 4.1. We label these as “hybrids” and “inbreds” to reflect the difference in yield levels, though we note there is nothing inherently hybrid or inbred about them.

Table 4.1 Specification of yield attribute levels used in discrete choice experiment

	Hypothetical seed yield distribution relative to local megavariety (Maunds per acre)					
Condition	Inbred first-order stochastic dominant	Inbred second-order stochastic dominant	Inbred third-order stochastic dominant	Hybrid first-order stochastic dominant	Hybrid second-order stochastic dominant	Hybrid third-order stochastic dominant
Normal	51	50	50	59	50	50
Moderate drought stress	32	32	26	36	36	26
Extreme drought stress	16	16	16	17	17	17

Source: Authors.
Note: A *maund* is a unit of mass commonly used in Bihar, equivalent to 40 kilograms.

Focus group discussions and consultations with scientists working on DT rice have indicated the importance of short durations to maturity for farmers in drought-prone areas since short durations provide a means of escaping drought (for example, if monsoon rains are delayed). Focus group discussions with farmers in several districts of Bihar have suggested that short duration remains an important attribute. In our choice experiment, we have incorporated duration to maturity (days from planting to harvest) as an attribute with three distinct levels, corresponding to short (less than 120 days), medium (120–135 days), and long (more than 135 days) duration.

Specifying drought tolerance through both dehydration tolerance and drought-escape mechanisms allows the researcher to determine which, if either, of these mechanisms is more valued by farmers, which in addition facilitates cost-benefit analysis that could inform public- and private-sector research and development programs in the discovery, development, and delivery of DT rice.

[10] Arvind Kumar leads the drought and aerobic rice-breeding program at the International Rice Research Institute.

Since we are interested in potential market segmentation, we also want to determine whether there are significant differences in the valuation between a DT hybrid and a DT variety. Heterosis is fully expressed in first-generation hybrid seeds but significantly declines in subsequent generations. Thus, farmers must purchase new hybrid seeds on a seasonal basis to obtain the maximum benefits conferred by heterosis. Varieties, on the other hand, maintain their performance for several generations, so harvested grains can generally be stored and reused as seeds in subsequent years. Therefore, to isolate the characteristic of nonreusability we characterize the choice as one between a seed that can be reused and a seed that cannot. This has been specified as a binary variable equal to one if grains can be stored and used as seeds and zero otherwise.[11]

We have also included an attribute to capture differences in the seeding rate between varieties and hybrids. Hybrids typically have significantly lower seeding rates than do varieties, sometimes on the order of 1:3. We specified two levels for the seeding rate, a low seeding rate (4–6 kilograms[kg]/acre) roughly corresponding to seeding rates for hybrids, and a high seeding rate (12–16 kg/acre) roughly corresponding to the seeding rates for conventional inbred varieties. As before, to avoid biasing responses, the unlabeled seeding rate ranges are presented to respondents in the choice sets.

Finally, an additional parameter capturing seed price was included to allow for the estimation of money metric measures for WTP and welfare comparisons. We have specified six price levels to be included in our choice sets. The price levels included have been specified based on cost and returns survey data collected in Bihar as part of the Cereal Systems Initiative for South Asia. The prices roughly correspond to prices at the 5th, 25th, 40th, 50th, 75th, and 99th percentiles of rice prices in these data. The actual prices included in the choice sets are 15, 25, 45, 140, 220, and 300 Indian rupees (Rs.).

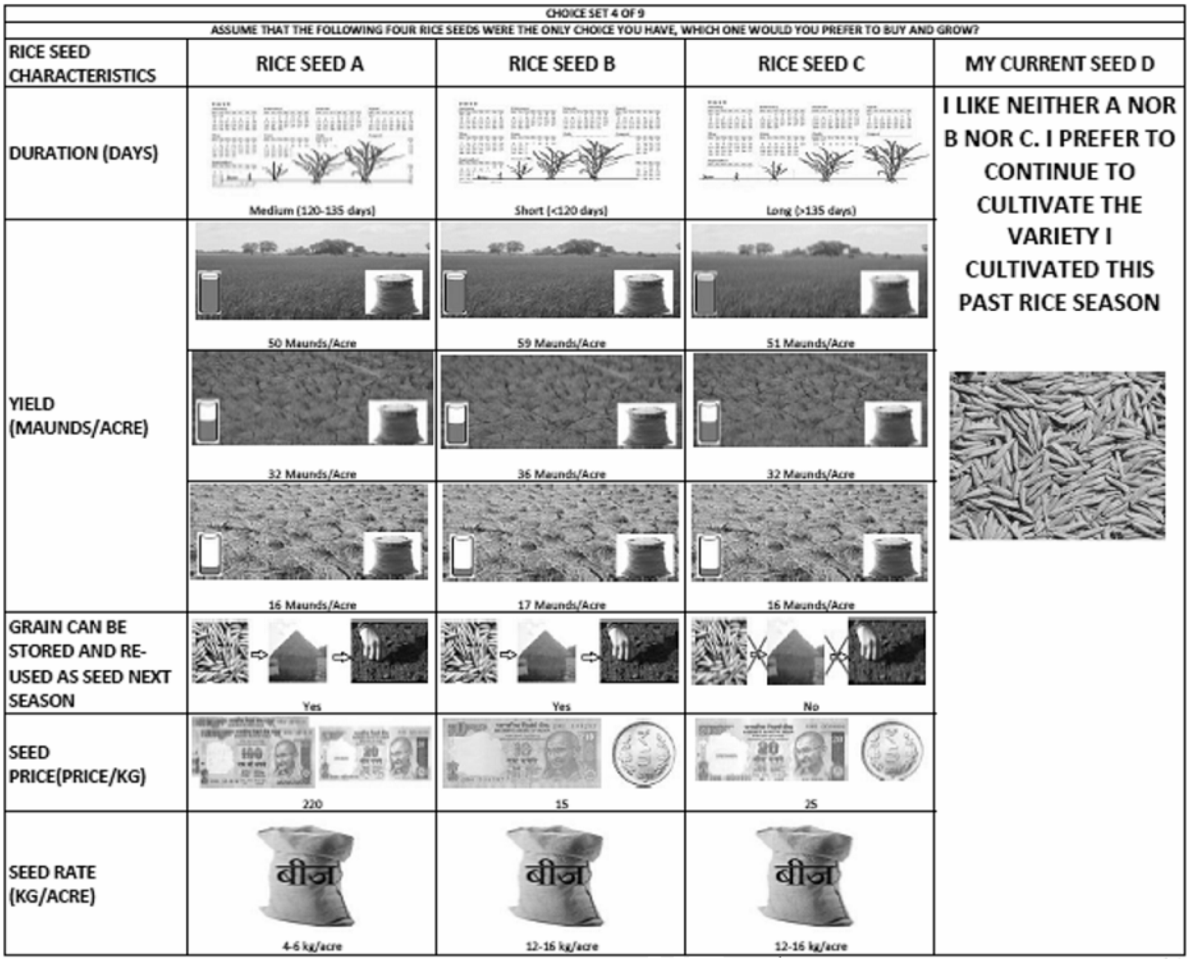
To construct our choice sets, we specified a D-optimal design that takes into account all main effects as well as interactions between the yield and seeding rate attributes with the binary reusability variable. The D-optimal design was achieved using a modified Federov search algorithm, with a full-factorial design constituting the candidate set. Choice sets were constructed with three alternatives per set, with a fourth option available to respondents whereby they choose to use the variety of rice they cultivated in the previous *kharif* season. Information about these "own varieties" is collected to allow us to control for attribute levels in the choice analysis.[12] To reduce the response burden on survey respondents and reduce the probability of respondent fatigue, the choice sets were blocked into four groups of nine choice sets each. Respondents were subsequently randomly assigned to respond to the choice tasks presented in one of these four groups, with an even number of households allocated to each of the groups. Illustrations were included in the choice sets to increase respondents' comprehension of the attributes and levels presented in the choice sets. An example of one of the choice sets is presented in Figure 4.2.[13]

[11] This choice was presented to participants in the experiment as a choice between seeds that would retain their yields if saved and planted in the subsequent season (that is, inbreds) and seeds that would lose their yield advantages if saved and planted in the subsequent season (that is, hybrids). This latter choice should not be viewed as a choice in which the saved seed is entirely sterile and will not germinate in the subsequent season, for example, as a result of introgression of a "terminator gene" in the plant. This controversial technology was not conveyed either directly or indirectly to the participants of the experiment.

[12] Although such information was used in the following analysis, it was not known during the experimental design, so the design proceeded assuming only three choice alternatives per choice set. By allowing respondents to opt out into simply reusing the seed they used last *kharif* season, we may introduce status quo bias; we note that only 11 percent of farmers in our sample chose this alternative. Thus, there does not appear to be a systematic overvaluation of the traits in their existing varieties.

[13] Although Figure 4.2 is shown in English, the actual choice sets presented to respondents were translated into Hindi to increase respondent comprehension.

Figure 4.2 Example of choice set presented to survey respondents



Source: Authors.

In addition to collecting data pursuant to the choice experiments, we also collected data from a series of experiments designed to ascertain farmers' preferences toward risk and potential losses. These experiments proceeded along the lines of those in Tanaka, Camerer, and Nguyen (2010) and Liu (2013). From these experiments, we estimated two parameters: σ which corresponds to the curvature of the prospect value function, and λ, which defines the degree of loss aversion. From cumulative prospect theory, the utility over a risky prospect with potential payouts $x$and y occurring with probabilities p and q= $1 - p$, respectively, is represented by

$$U(x, y; p, q, \sigma, \lambda) = \begin{cases} v(y) + w(p)[v(x) - v(y)] & \text{for } |x| > |y| > 0 \\ w(p)v(x) + w(q)v(y) & \text{for } x < 0 < y \end{cases}$$

where $v(\cdot)$ is the value function for the various risky outcomes and $w(\cdot)$is a probability weighting function (with parameter α) that captures the degree to which low-probability extreme outcomes are overweighed when risky prospects are evaluated. The value function is specified according to

$$v(x) = \begin{cases} x^{\sigma} & \text{for } x > 0 \\ -\lambda(-x)^{\sigma} & \text{for } x < 0 \end{cases}$$

and the probability-weighting function is the axiomatically derived weighting function in Prelec (1998): $w(p) = \exp[-(-\ln p)^{\alpha}]$. Other things being equal, for $0 < \sigma < 1$, value function curvature is decreasing in σ, thus implying that risk aversion increases as σ decreases. Values of σequal to unity imply risk neutrality for nonnegative prospects, whereas values of σ greater than unity imply risk-seeking behavior over nonnegative prospects.

As a final component of this study, we conducted a household survey to collect information about, among other things, household characteristics (including demographic and socioeconomic characteristics), agricultural production, and experiences with both positive and negative economic shocks (including droughts). These additional sources of information are relevant for further understanding the determinants of WTP, especially as it pertains to preference heterogeneity, both between and within households. Table 4.2 summarizes the households in our sample on some of these important dimensions, including preferences over risk and potential losses.

Table 4.2 Summary statistics characterizing farmers in sample

Variable	Bhojpur	Madhubani	Nawada
σ (value function curvature)	0.775	0.636	0.813
	(0.389)	(0.378)	(0.430)
λ (loss aversion)	3.593	7.948	3.100
	(2.930)	(3.332)	(3.042)
Age (years)	48.389	46.110	47.602
	(13.846)	(13.052)	(14.126)
Household size (number of persons)	6.553	6.089	6.777
	(3.018)	(3.035)	(2.937)
Land area owned during *kharif* 2012 (acres)	2.429	1.454	1.570
	(4.475)	(2.154)	(1.480)
Land area shared during *kharif* 2012 (acres)	0.519	0.417	0.291
	(1.263)	(0.823)	(0.577)
Land area rented in during *kharif* 2012 (acres)	0.627	0.129	0.014
	(2.087)	(0.551)	(0.141)
Land area rented out during *kharif* 2012 (acres)	0.223	0.046	0.085
	(1.793)	(0.347)	(0.567)
Land area left fallow during *kharif* 2012 (acres)	0.115	0.705	0.077
	(0.412)	(1.870)	(0.248)
Household rice farming experience (years)	63.845	46.308	58.456
	(42.178)	(40.933)	(43.066)
Number of different varieties cultivated during *kharif* 2012	1.358	1.658	1.369
	(0.533)	(0.699)	(0.524)
Number of new rice varieties cultivated in the past five years	0.880	1.726	0.796
	(1.198)	(0.757)	(1.278)
Number of plots on which rice was cultivated during *kharif* 2012	1.835	1.973	1.631
	(0.911)	(0.989)	(0.792)
Total consumption expenditures during 2012 (Rs.)	73,231.810	35,606.920	62,696.120
	(54,188.000)	(29,062.220)	(38,920.480)
Number of negative income shocks experienced in past five years	0.779	0.767	0.718
	(1.121)	(2.068)	(1.097)
Total damages from shocks experienced in past five years (Rs.)	44,308.410	16,715.750	12,737.860
	(146,564.200)	(54,183.500)	(32,374.630)
Subsample size	226	146	103

Source: Authors.

Note: Rs. = Indian rupees.

5. RESULTS

The results of estimating the random parameters logit model represented by equation (7) are reported in Table 5.1. We first estimated the model ignoring the possible influences of risk and loss aversion in conditioning choice probabilities, followed by a similar regression in which these influences are accounted for. Where these terms are included, they enter as alternative-specific variables and therein measure the effects of risk and loss aversion on choice probabilities for specific alternatives relative to the omitted alternative. In other words, these parameters enter as shifters of the utility derived from an observed choice. Including these terms in this fashion explicitly acknowledges the role of risk and loss aversion in farmer utility functions.[14] These results are shown in columns (I) and (II) of Table 5.1, respectively. For each regression, we report two sets of results: the first set (top panel) provides mean values for the marginal utility parameters, and the second set (lower panel) provides estimates of the standard deviation for the normally distributed parameters. The former provides us with insight into the relative value associated with each of the attribute levels, and the latter provides us with information about the shape of the parameter distributions, which in turn gives insight into the degree of preference heterogeneity.

Two interesting observations emerge when comparing the two sets of results reported in columns (I) and (II). First, from column (II), we see that σ_A-σ_C and λ_A-λ_C are highly statistically significant, indicating that on average, σ and λ significantly affect the probability that seed alternatives A through C—which all demonstrate some degree of stochastic dominance over common local megavarieties—will be chosen in lieu of alternative D, which is the option of simply cultivating the same variety as in the previous *kharif* season. Specifically, the coefficients associated with σ_A-σ_C are all negative, whereas the coefficients associated with λ_A-λ_C are all positive. This implies that increasing degrees of risk aversion (that is, lower σ) and loss aversion (that is, higher λ) increase the probability that a respondent would opt to switch to one of the hypothetical DT seeds rather than cultivating the same variety as in the previous *kharif*. Because of differences in scale, it is difficult to make judgments as to which is more important in this result. Given the average σ in the sample is 0.74 and the average λ in the sample is 4.82, it could reasonably be suggested that risk aversion is more crucial in conditioning these choices. This result could arise either because less risk-averse individuals are perhaps more likely to have adopted improved seeds—implying that the relative benefits of the hypothetical DT seeds embodied in alternatives A through C are less for these farmers than for more risk-averse farmers—or because risk-averse farmers are particularly sensitive to drought risk and value the yield gains under moderate or severe drought stress offered by the hypothetical DT seeds.

The lower panel of Table 5.1 demonstrates the heterogeneity in farmers' preferences for these various rice seed attributes. All of the estimated standard deviations are statistically significant, indicating a clear rejection of homogeneous preferences (that is, fixed coefficients) for these attribute levels. Across both regressions, the estimated standard error for not being able to store harvested grain and use it as seed is larger than any of the other estimated standard deviations, suggesting there are wide variations in how farmers in our sample feel about this trait that is characteristic of hybrids. The estimated standard error of the distribution of marginal utility parameters for the hybrid FSD yield distribution is the second largest estimated standard error across these two regressions, suggesting a great degree of preference heterogeneity for this characteristic.

[14] For simplification, we incorporate these parameters additively in the utility function, rather than the more common practice of introducing risk aversion in an exponential or power form, and incorporating loss aversion multiplicatively.

Table 5.1 Random parameters logit results

	(1)			(2)		
	Estimate		Standard error	Estimate		Standard error
Random utility parameters						
Yields 51, 32, 16[a] maunds/acre (inbred FSD)	1.726	***	0.097	2.290	***	0.196
Yields 50, 32, 16[a] maunds/acre (inbred SSD)	1.635	***	0.099	2.224	***	0.200
Yields 50, 26, 16[a] maunds/acre (inbred TSD)	1.464	***	0.097	2.046	***	0.199
Yields 59, 36, 17[a] maunds/acre (hybrid FSD)	2.326	***	0.130	2.917	***	0.214
Yields 50, 36, 17[a] maunds/acre (hybrid SSD)	1.871	***	0.104	2.431	***	0.201
Yields 50, 26, 17[a] maunds/acre (hybrid TSD)	1.711	***	0.102	2.223	***	0.201
Short duration (less than 120 days)	0.179	***	0.069	0.202	***	0.069
Medium duration (120–135 days)	0.213	***	0.061	0.205	***	0.063
Low seeding rate (4–6 kilograms/acre)	0.721	***	0.055	0.679	***	0.056
Grain cannot be stored and reused as seed	–0.634	***	0.087	–0.658	***	0.088
Nonrandom marginal utility parameters						
Price	–0.011	***	0.000	–0.011	***	0.000
Alternative-specific parameters						
σ_A				–1.243	***	0.178
σ_B				–1.322	***	0.182
σ_C				–1.414	***	0.180
λ_A				0.107	***	0.021
λ_B				0.135	***	0.021
λ_C				0.103	***	0.021
Distribution parameters						
Standard deviation (inbred FSD)	0.647	***	0.160	0.546	***	0.166
Standard deviation (inbred SSD)	0.686	***	0.132	0.635	***	0.134
Standard deviation (inbred TSD)	0.577	***	0.146	0.596	***	0.145
Standard deviation (hybrid FSD)	1.569	***	0.164	1.540	***	0.155
Standard deviation (hybrid SSD)	0.884	***	0.139	0.807	***	0.141
Standard deviation (hybrid TSD)	0.857	***	0.136	0.811	***	0.136
Standard deviation (short duration)	0.944	***	0.082	0.898	***	0.083
Standard deviation (medium duration)	0.567	***	0.101	0.576	***	0.099
Standard deviation (grain cannot be stored and reused as seed)	1.637	***	0.097	1.660	***	0.098
Standard deviation (low seeding rate)	0.591	***	0.074	0.616	***	0.072
Log-likelihood	–4,298.616			–4,233.410		

Source: Authors.

Notes: FSD = first-order stochastically dominant; SSD = second-order stochastically dominant; TSD = third-order stochastically dominant. * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Presented models were estimated using NLOGIT 5.0.

[a] These figures correspond to yields under normal conditions, moderate drought stress conditions, and extreme drought stress conditions, respectively.

The second observation that can be made from comparing the results in columns (I) and (II) supports this latter argument. Once we control for the roles of risk and loss aversion in conditioning choice probabilities, the marginal utility associated with the different yield distributions increases rather substantially. And it is not just the marginal utility of the FSD yield distributions that increase. The valuation of all distributions increase, suggesting that the farmers in our sample appreciate the reduction in variance and kurtosis embodied in the hypothetical DT alternatives. But although the yield distribution attributes become more attractive once we control for the effects of risk and loss aversion in conditioning seed choices, the marginal utility of other attributes remain roughly unchanged. This is clearly seen in Figure 5.1 and Figure 5.2, which plot kernel density estimates of the empirical distributions of the random parameters for the different yield and nonyield attributes, respectively. In Figure 5.1, there is a clear shift in the distribution of the random parameters for the different yield distribution attributes, implying a higher mean marginal utility for each of these DT yield distributions. In Figure 5.2, the distributions are virtually indistinguishable from one another, suggesting perhaps that the marginal utilities for these nonyield attributes are drawn from the same data-generating process, regardless of whether risk and loss aversion are allowed to condition the choice probabilities in the discrete choice experiment.

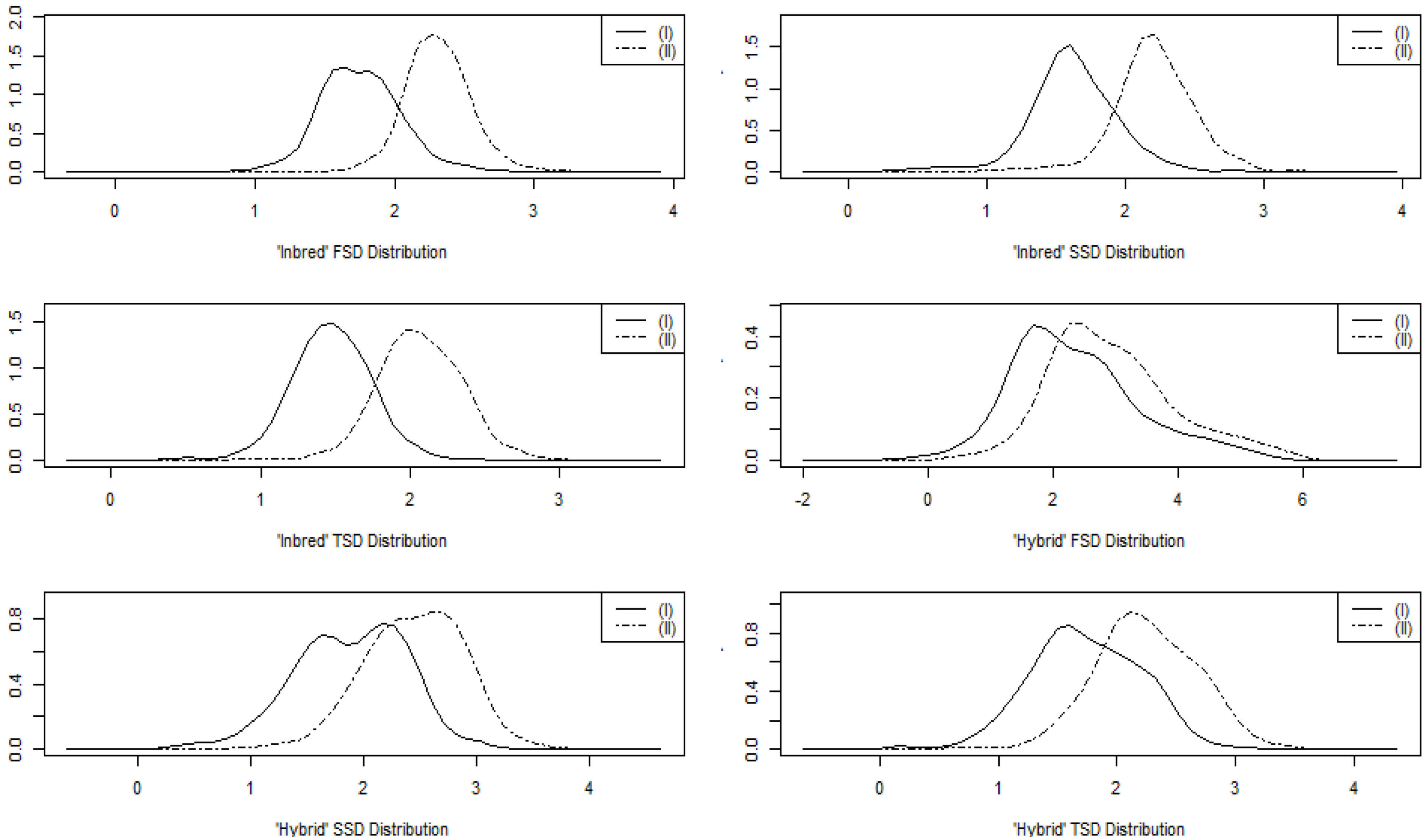
The mean marginal utilities for each of the yield distribution attribute levels are positive in both regressions. This is as expected since these yield distributions stochastically dominate the distributions of megavarieties commonly grown in eastern India. In both regressions, the marginal utility of an FSD distribution is higher than that of an SSD distribution, which in turn is higher than that of a TSD distribution. This result implies that farmers prefer higher expected yields over and above lower yield variability or protection against low probability downside risk (similar to Lybbert 2006).

In addition, the marginal utility for the hybrid seed distributions is always and everywhere higher than the marginal utility for the corresponding inbred distributions.[15] This, again, is not particularly surprising, since although both exhibit the same degree of stochastic dominance over check varieties, the hybrid yields are at least as high as the inbred yields under all conditions and higher than the inbred under at least one condition. So the hybrid yield distributions stochastically dominate the inbred distributions to the same degree to which they both dominate the local megavariety. For example, the hybrid FSD yield distribution actually also stochastically dominates the inbred FSD yield distribution in the first order, the hybrid SSD yield distribution stochastically dominates the inbred SSD yield distribution in the second order, and so on.

Both short and medium durations have positive marginal utilities, suggesting that farmers prefer these both relative to long durations. But there is not an appreciable difference in the marginal utilities between these two: Contrary to what might be expected, farmers do not have a demonstrably higher valuation for short-duration paddy, which would allow the farmer to grow a crop to duration even in the event of delayed monsoon rains.

[15] For example, the marginal utility of an FSD "hybrid" yield distribution is higher than the marginal utility of an FSD "inbred" yield distribution.

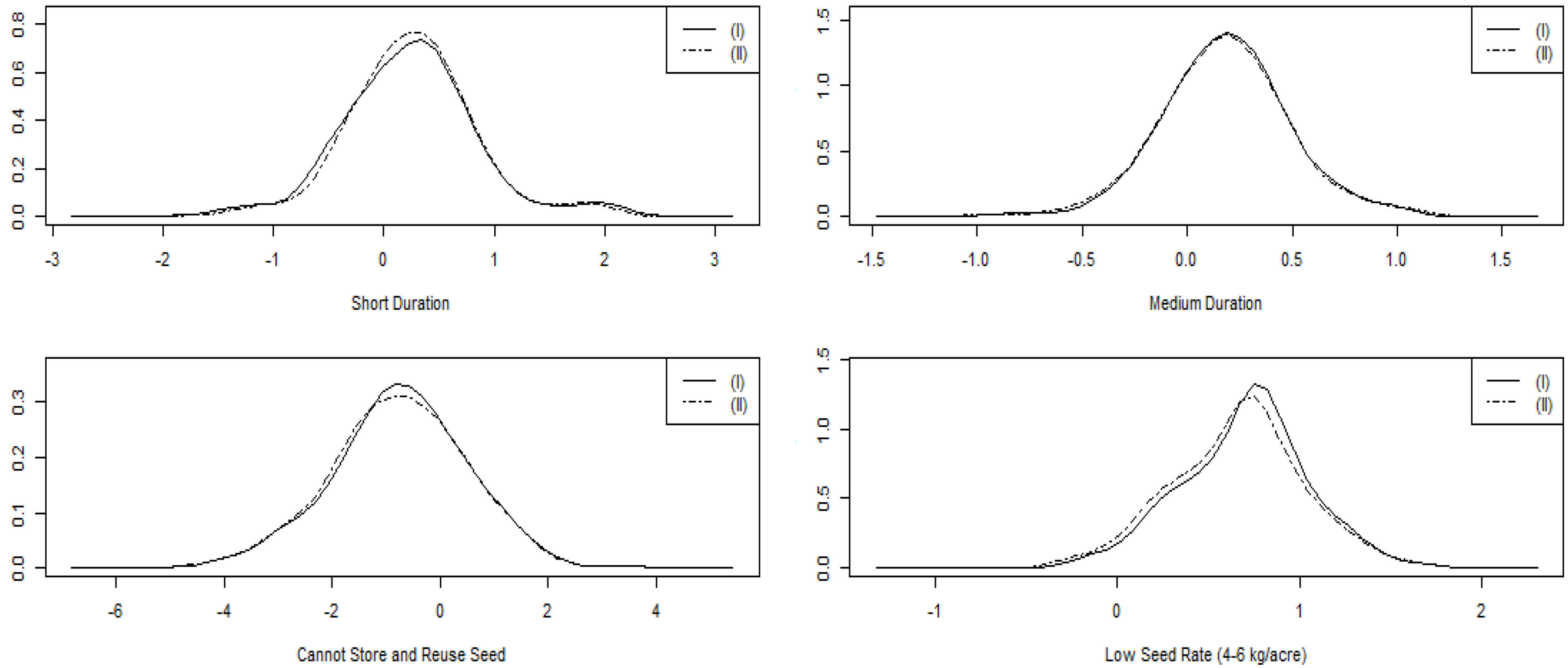
Figure 5.1 Random parameter distributions for yield distribution attributes, (I) without and (II) with risk- and loss-aversion conditioning choice probabilities



Source: Authors.

Note: FSD = first-order stochastically dominant; SSD = second-order stochastically dominant; TSD = third-order stochastically dominant.

Figure 5.2 Random parameter distributions for nonyield attributes, (I) without and (II) with risk- and loss-aversion conditioning choice probabilities



Source: Authors.

As expected, in both regressions the marginal utility of price is negative, indicating that farmers generally prefer cheaper seeds to more expensive seeds. This term can be used to generate money-metric WTP figures for each of the attribute levels using equation (6). The estimated WTPs associated with each of these attribute levels are given in Table 5.2. We use a parametric bootstrapping procedure (Krinsky and Robb 1986) to generate 95 percent confidence intervals for these estimates.

Table 5.2 Estimated willingness-to-pay for rice seed attributes, random parameters logit

Description	(I)			(II)		
	Lower 2.5%	Mean	Upper 2.5%	Lower 2.5%	Mean	Upper 2.5%
Yields 51, 32, 16 maunds/acre (inbred FSD)	136.583	154.241	172.786	168.711	199.988	229.480
Yields 50, 32, 16 maunds/acre (inbred SSD)	128.767	146.243	163.654	161.987	193.957	228.092
Yields 50, 26, 16 maunds/acre (inbred TSD)	113.980	130.992	148.150	144.893	178.699	211.272
Yields 59, 36, 17 maunds/acre (hybrid FSD)	186.824	208.033	231.438	219.274	254.618	290.601
Yields 50, 36, 17 maunds/acre (hybrid SSD)	148.231	167.303	186.212	180.551	212.267	245.691
Yields 50, 26, 17 maunds/acre (hybrid TSD)	134.693	153.638	171.418	159.934	194.134	227.664
Short duration (less than 120 days)	3.549	16.017	28.072	5.900	17.363	29.470
Medium duration (120–135 days)	8.579	19.055	30.285	7.056	17.724	28.620
Low seeding rate (4–6 kilograms/acre)	54.979	64.657	74.063	49.548	59.418	69.307
Grain cannot be stored and reused as seed	–71.525	–56.739	–42.118	–73.126	–57.532	–43.113

Source: Authors.

Note: FSD = first-order stochastically dominant; SSD = second-order stochastically dominant; TSD = third-order stochastically dominant. Confidence intervals derived using parametric bootstrap procedure introduced in Krinsky and Robb (1986) based on 1,000 random draws from a multivariate normal distribution with means and variance-covariance matrix of the estimated model parameters.

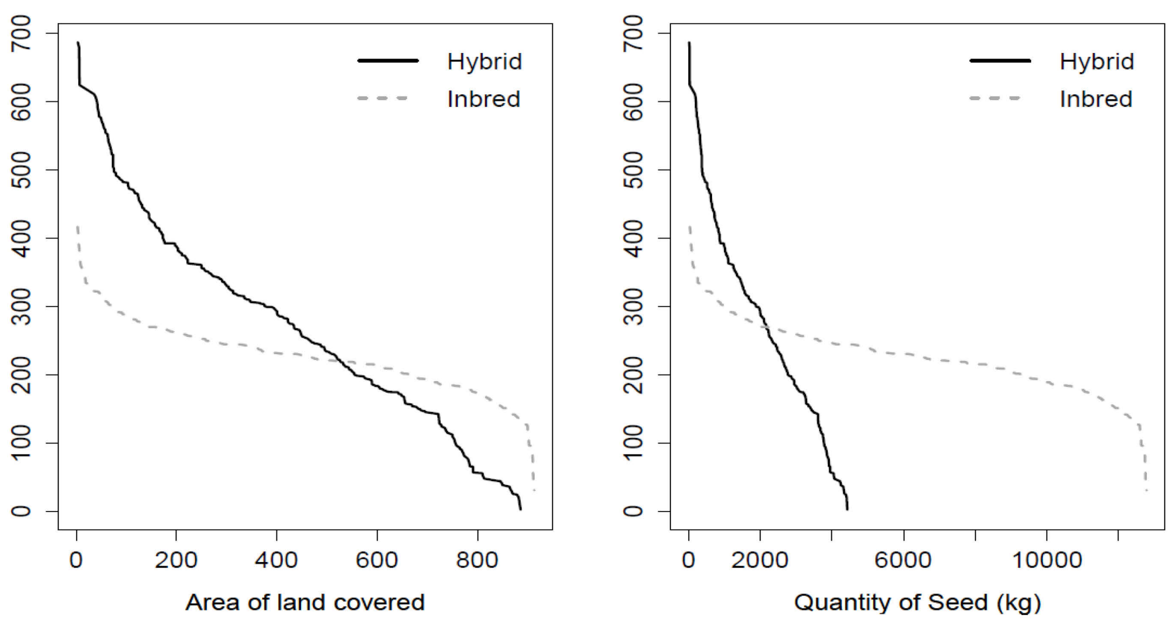
For the six DT yield distribution levels, incorporating risk and loss aversion into the utility function raises WTP by approximately Rs.45 at each level, whereas there is virtually no change in WTP for the nonyield attributes (duration, seeding rate, or whether the harvest grains can be stored and reused for seed). When risk and loss aversion condition utility, estimates suggest that farmers would be willing to pay Rs.200 for a DT seed yielding 51, 32, and 16 maunds per acre under normal, moderate stress, and severe stress conditions, respectively (that is, inbred FSD), whereas farmers would be willing to pay Rs.255 for a DT seed yielding 59, 36, and 17 maunds per acre under normal, moderate drought stress, and severe drought stress conditions, respectively (that is, hybrid FSD). These figures seem high, considering the average cost of seed among farmers in our sample, but they highlight the extent to which farmers value DT characteristics.[16] We estimate, therefore, that farmers are willing to pay a premium of approximately Rs.55 for the additional yield under all conditions. For a DT seed yielding 50, 36, and 17 maunds per acre under normal, moderate drought stress, and severe drought stress conditions, respectively (hybrid SSD), farmers are willing to pay roughly Rs.212—more than for the inbred FSD that yields more under normal conditions (51 versus 50 maunds per acre) but less under moderate drought stress conditions (32 versus 36 maunds per acre) and severe drought stress conditions (16 versus 17 maunds per acre). Although the confidence intervals for these two WTP estimates overlap to some degree, these estimates suggest that farmers in our sample value a reduction in risk (that is, increased yields under stress conditions), even at the expense of a reduction in mean (that is, reduced yields under normal conditions). Indeed, comparing the mean and confidence interval for WTP for the inbred FSD distribution with the mean and confidence interval for WTP for the hybrid TSD distribution (which has lower expected yields,

[16] For comparison, the average price of rice seed cultivated during kharif 2012 among the farmers in our sample is only Rs.42.69.

lower yields under moderate stress conditions, but an additional 1 maund per acre under severe stress conditions) gives insight into the relative valuation of protection against downside risk in the extreme tails of the weather-yield distribution. Farmers are roughly willing to pay the same for a seed that yields 50, 26, and 17 maunds per acre under normal, moderate drought stress, and severe drought stress conditions (hybrid TSD), respectively, as they are for one that yields 51, 32, and 16 maunds per acre (inbred FSD). Since farmers value these two yield distributions roughly equivalently, this suggests a tradeoff between higher expected and less-variable yields and the additional protection against severe droughts.

We can bundle WTP estimates for a series of attributes and gauge an approximate value for how much farmers would be willing to pay for a particular seed containing that combination of attributes. For example, we might be interested in determining how much farmers would be willing to pay for a short-duration DT hybrid that yields 59, 36, and 17 maunds per acre under normal, moderate drought stress and severe drought stress conditions, respectively. To do so, we would simply add the WTP for the attributes that are embodied in this hypothetical seed. Since it is a DT hybrid, in addition to valuations for short duration and the hybrid FSD yield distribution, we would take into consideration the valuations for both a low seeding rate and the inability to store harvested grain and use it as seed, two features characteristic of hybrids. Since each individual is assumed to have unique preferences for each of the attributes, each individual would also have a unique WTP for this bundle. These WTPs can be sorted and ranked from highest to lowest and plotted against some measure of quantity to illustrate the demand for a particular seed bundle at various prices. Figure 5.3 plots two sets of demand curves, with area under cultivation and quantity of seed used along the horizontal axis. In each plot, two demand curves are presented, one corresponding to a hypothetical DT hybrid (as described above) and one corresponding to a DT variety similar to IRRI's Sahbhagi dhan.

Figure 5.3 Demand curves for a hypothetical drought-tolerant hybrid and a drought-tolerant variety similar to International Rice Research Institute's Sahbhagi dhan



Source: Authors.

Plotting WTP against seed quantity complicates comparisons between the demand structures between a DT hybrid and a variety. There are inherent differences in seeding rates between hybrids and varieties, such that farmers would require a lower quantity of hybrids than varieties to cultivate a given area of land. Other things being equal, therefore, farmers would have to purchase a larger quantity of inbred seeds than they would hybrids. But this would be only for the first year since varieties can be stored and reused as seeds in later years. Farmers cultivating DT hybrids would use a lower quantity of seed but would have to purchase new seed every year.

From these demand curves, we see there is a great deal of heterogeneity in demand for DT hybrids and DT varieties. Demand for DT hybrids is both much more heterogeneous and much more inelastic. WTP for a DT hybrid ranges from nearly Rs.700 to actually negative values for some farmers (not shown in Figure 5.3). But to significantly increase the area under cultivation, the price would have to decline markedly. Such is not the case for a DT variety. The range of WTP for a DT variety is much narrower, implying much more uniform valuations among the farmers in our sample.

The differences in demand structures for the DT hybrid and DT variety suggest a role for both private-sector DT hybrids and DT varieties developed by the public sector. Rather than necessarily competing, these two seeds could serve different segments of the market. Furthermore, this natural segmentation suggests the potential for transformative public-private partnerships in the discovery, development, and delivery of DT technologies.

We can also introduce preference heterogeneity through the use of latent class modeling, following equation (10). We consider two methods for class segmentation: random class segmentation and segmentation based on farmer characteristics that might be important in distinguishing farmer preferences, such as age, experience with rice cultivation, experimentation or diversification with different rice varieties, and agricultural income. The optimal number of classes is determined by comparing diagnostics for models with different numbers of classes, but a balance must generally be reached between the importance of the different diagnostic measures. Model diagnostics are reported in Table 5.3 for models with two to five classes under both methods of class segmentation. In both cases, the model with three classes has better log-likelihood, pseudo R^2, and Akaike Information Criterion, but there are concerns that a three-class model overfits the data since one of the resulting class probabilities (in the random model) is less than 5 percent and the estimated marginal utility parameters for some of the attributes within this class are generally unrealistic. Under both specifications, the two-class model results in the lower (and therefore better) Bayesian Information Criterion, which Nylund, Asparouhov, and Muthen (2007) have suggested is the more appropriate model diagnostic to use in determining the number of classes in latent class analysis. We thus proceed with estimating a two-class model, the results of which are reported in Table 5.4.

Table 5.3 Latent class diagnostics

Class	k	Log-likelihood	Pseudo R^2	AIC	BIC
	Random class membership				
1	17	–4566.968	.229	9167.935	4638.032
2	35	–4083.209	.311	8236.419	4229.519
3	53	–4023.534	.321	8153.067	4245.088
4	71	–4163.272	.298	8468.544	4460.071
5	89	–4105.466	.307	8388.933	4477.510
	Class membership conditioned by age, rice experience, number of varieties cultivated in 2012, and ln(agricultural income)				
Class	**k**	**Log-likelihood**	**Pseudo R^2**	**AIC**	**BIC**
1	17	–4566.968	.229	9167.935	4638.032
2	39	–4121.170	.305	8320.340	4284.201
3	61	–4096.610	.309	8315.220	4351.606
4	83	–4163.970	.297	8493.940	4510.932
5	105	–4157.030	.299	8524.060	4595.958

Source: Authors.

Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. These statistics were based on a sample of 4,275 choices from 475 farmers (each making 9 choices). McFadden's pseudo R^2 is computed as $1 - LL/LL(0)$, where $LL(0)$ is the log-likelihood for a restricted model (only including an intercept). AIC is computed as $-2(LL - k)$, where k is the number of parameters estimated. BIC is computed as $[\ln(\mathrm{N}) \times k/2] - LL$, where N is the sample size.

It is often valuable to identify the sources of class segmentation arising from the latent class modeling approach. Such identification often arises from differences in the marginal utility parameter estimates. In our case, since we control for risk and loss preferences in the utility function, we are also able to define class segmentation in class members' sensitivity to risks and losses. For example, in both the random and the conditional latent class models, members of class 1 are significantly more sensitive to losses than they are to risks. Indeed, given the lack of statistical significance for the effects of $\sigma_A - \sigma_C$, one could argue that risk preferences play no role whatsoever in conditioning seed choices for these farmers. But given the degree to which their choices are conditioned by aversion to potential losses (for example, those arising from droughts), class 1 members have substantially higher marginal utilities for the DT yield distribution attributes. Class 2 members, on the other hand, although somewhat sensitive to losses, are much more sensitive to risks. But surprisingly, they do not seem to value the reduction in yield variability or protection against extreme tail events offered by the SSD and TSD distributions. This is particularly true in the random latent class model, in which the marginal utility of TSD distributions is not statistically different from zero and only the marginal utility of the hybrid SSD distribution is statistically significant.

Table 5.4 Latent class model estimates

Description	Random latent class model						Conditional latent class model					
	Class 1			Class 2			Class 1			Class 2		
	Coefficient		Standard error	Coefficient		Standard error	Coefficient		Standard error	Coefficient		Standard error
Utility parameters												
Yields 51, 32, 16 maunds/acre (inbred FSD)	1.861	***	0.257	0.936	***	0.238	1.925	***	0.188	0.900	***	0.118
Yields 50, 32, 16 maunds/acre (inbred SSD)	1.767	***	0.258	0.314		0.266	1.826	***	0.205	0.288	**	0.137
Yields 50, 26, 16 maunds/acre (inbred TSD)	1.701	***	0.256	0.326		0.257	1.762	***	0.198	0.294	*	0.155
Yields 59, 36, 17 maunds/acre (hybrid FSD)	2.237	***	0.271	1.641	***	0.284	2.269	***	0.194	1.631	***	0.107
Yields 50, 36, 17 maunds/acre (hybrid SSD)	2.127	***	0.263	0.829	***	0.255	2.192	***	0.215	0.808	***	0.122
Yields 50, 26, 17 maunds/acre (hybrid TSD)	2.043	***	0.265	–0.007		0.276	2.115	***	0.191	–0.018		0.163
Short duration (less than 120 days)	0.318	***	0.073	0.251	**	0.098	0.317	***	0.068	0.257	***	0.062
Medium duration (120–135 days)	0.150	**	0.070	0.171	**	0.087	0.144	*	0.074	0.185	***	0.060
Low seeding rate (4–6 kilograms/acre)	0.597	***	0.057	0.405	***	0.077	0.608	***	0.055	0.394	***	0.060
Grain cannot be stored and reused as seed	–1.199	***	0.089	0.189	*	0.101	–1.205	***	0.062	0.155	***	0.051
Price	–0.016	***	0.001	–0.001	**	0.000	–0.016	***	0.000	–0.001	***	0.000
Parameters conditioning choice probabilities												
σ_A	–0.151		0.230	–1.403	***	0.219	–0.184		0.163	–1.367	***	0.126
σ_B	–0.273		0.237	–1.539	***	0.228	–0.311	*	0.173	–1.506	***	0.161
σ_C	–0.236		0.231	–1.750	***	0.236	–0.266	*	0.161	–1.705	***	0.165
λ_A	0.198	***	0.032	0.113	***	0.026	0.192	***	0.026	0.118	***	0.015
λ_B	0.243	***	0.033	0.112	***	0.027	0.239	***	0.028	0.117	***	0.018
λ_C	0.228	***	0.032	0.100	***	0.028	0.224	***	0.026	0.106	***	0.018
Parameters conditioning class membership												
Constant							1.400	*	0.782			
Age							–0.011		0.009			
Number of years of experience cultivating rice							–0.006	*	0.003			
Number of different varieties cultivated in *kharif* 2012							–0.225		0.200			
ln (agricultural income)							0.072		0.054			
Probability of class membership	.721			.279			.713			.287		
Log-likelihood												

Source: Authors.

Note: FSD = first-order stochastically dominant; SSD = second-order stochastically dominant; TSD = third-order stochastically dominant.* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Presented models were estimated using NLOGIT 5.0.

Members of class 1 are also sensitive about being able to save their harvested grains and use them as seed in future *kharif* seasons. These farmers have large and highly significant negative marginal utilities associated with having to purchase new seeds every year. Farmers in class 2, on the other hand, have positive marginal utilities for having to purchase new seed every year, perhaps suggesting that they have an understanding of the many benefits of first-generation seeds over seeds from second or later generations.

It might be tempting to compare the magnitudes of the marginal utilities for, for example, the hybrid FSD yield distribution and conclude that members of class 1 would be willing to pay more for a seed with this distribution, but such a conclusion fails to observe differences in price sensitivity between the two classes. Farmers in class 1 are dramatically more price sensitive than farmers in class 2, as their marginal disutility of price is more than 10 times the marginal disutility of price for farmers in class 2. The very low (in magnitude) marginal disutility of price for farmers in class 2 may partly explain why farmers in this class have positive marginal utilities associated with purchasing new seed every year.[17] Since the marginal disutility of price is in the denominator of WTP estimates, these differences in the marginal disutility of price have important implications for multiclass segmented demand. Table 5.5 reports WTP for each of the various rice seed attributes across both classes, along with corresponding 95 percent confidence intervals. For these estimates, we draw only from the random latent class model results, though we note there are no appreciable differences in the estimates when farmer characteristics are introduced to condition class segmentation.

Table 5.5 Estimated willingness-to-pay for seed attributes, random latent class model

Description	Class 1			Class 2		
	Lower 2.5%	Mean	Upper 2.5%	Lower 2.5%	Mean	Upper 2.5%
Yields 51, 32, 16 maunds/acre (inbred FSD)	83.103	115.196	147.156	345.123	1135.126	4323.970
Yields 50, 32, 16 maunds/acre (inbred SSD)	75.697	109.714	141.546	–527.054	320.516	1473.036
Yields 50, 26, 16 maunds/acre (inbred TSD)	74.708	105.596	138.800	–397.207	359.064	1739.085
Yields 59, 36, 17 maunds/acre (hybrid FSD)	100.630	139.199	178.705	790.487	1971.960	7426.097
Yields 50, 36, 17 maunds/acre (hybrid SSD)	97.959	131.897	163.494	244.027	950.453	3436.853
Yields 50, 26, 17 maunds/acre (hybrid TSD)	92.376	126.731	160.091	–1141.437	–85.206	759.737
Short duration (less than 120 days)	11.119	19.513	28.214	36.582	325.698	1273.338
Medium duration (120–135 days)	0.390	9.344	17.969	–39.182	226.337	913.926
Low seeding rate (4–6 kilograms/acre)	30.003	37.080	44.190	158.349	526.303	2034.961
Grain cannot be stored and reused as seed	–83.625	–74.210	–64.872	–32.393	237.554	1122.333

Source: Authors.

Note: FSD = first-order stochastically dominant; SSD = second-order stochastically dominant; TSD = third-order stochastically dominant. Confidence intervals were derived using parametric bootstrap procedure introduced in Krinsky and Robb (1986) based on 1,000 random draws from a multivariate normal distribution with means and variance-covariance matrix of the estimated model parameters

[17] We note that even though farmers in class 2 have a smaller marginal utility of price (less negative), this should not be construed as implying that these farmers are wealthier and are therefore less concerned with price. When we allow covariates to condition class membership, we find that households with higher agricultural incomes are no more likely to be members of class 2 than of class 1. The point estimate suggests that farmers with more agricultural income are actually more likely to be members of class 1 than class 2, though this point estimate is not statistically different from zero at standard significance levels.

These WTP estimates should likely be viewed with caution. Clearly, the estimates of WTP for the various seed attributes for class 2 are excessive and largely infeasible. This is largely driven by the very small marginal disutility of price for this class of farmers. Few farmers—even extremely wealthy ones—would likely be willing to pay nearly Rs.2,000 per kg for rice seed, even if such seed yields 59 maunds per acre under normal conditions and 36 maunds per acre during moderate droughts. There are generally very wide confidence intervals for the valuations of the seed attributes for class 2, leading to imprecise measurements of WTP. Several of the empirical distributions span 0, so we cannot be confident even of the sign of the WTP estimate for these attribute levels.

In simplest terms, these results confirm our previous findings of significant heterogeneity in preferences over rice seed characteristics. The estimates also suggest a great deal of heterogeneity in the valuation of DT characteristics. Across both classes, there are positive and significant WTPs for DT seeds whose yield distributions are higher than local megavarieties under all conditions. But farmers in class 2 do not seem to highly value seeds that merely reduce yield variability or provide additional protection against severe droughts, despite their seed choices' being particularly sensitive to the farmers' preferences for risk and, to a lesser degree, the potential for losses.

In addition, the latent class modeling approach further supports our previous findings about the potential for both public-sector DT varieties and private-sector DT hybrids to coexist and the potential for public-private partnerships in developing these technologies. Within both classes, there is potentially significant demand for DT, especially DT rice that also provides yield advantages under normal conditions (that is, a yield distribution that first-order stochastically dominates other varieties). Famers in class 2 exhibit a small disutility of price and a positive marginal utility of purchasing new seed every year, suggesting a natural market segment that could be specifically targeted by private-sector DT hybrids. Farmers in class 1, on the other hand, are far more sensitive to price and exhibit a significant disutility when it comes to purchasing new seed every year.

6. CONCLUSION

In this study, we use discrete choice experiments to examine farmers' preferences for DT traits embodied in different rice backgrounds and model heterogeneity in these preferences using both random parameters (capturing preference heterogeneity at the individual level) and latent class (capturing preference heterogeneity across multiple classes of farmers) modeling approaches. This research provides a novel analysis of demand for new, pro-poor technologies and demonstrates that natural heterogeneity also presents natural market segmentation such that both public-sector DT varieties and DT hybrids developed by the private sector could coexist in the market, thereby making the benefits of these technologies more widely accessible to poor and vulnerable farmers who would benefit the most from them.

In our discrete choice experiment, we present DT through a series of yield distributions, with yields under normal conditions (that is, expected yields), moderate drought stress conditions, and severe drought stress conditions. This method explicitly illustrates that seeds represent a bundle of potential yields—not just an average yield—including a range of yields under suboptimal conditions. Although many seed companies and research institutions focus on yields under normal conditions, risk-averse farmers would also be expected to care about yield variability and exposure to extreme weather events rather than only focusing on expected yields. Our empirical results support this. We find that there is significant demand for DT characteristics. Although farmers are willing to pay more for rice seed that yields more than local megavarieties in all conditions, they are also willing to pay significant amounts for seeds that outperform these megavarieties under drought stress conditions, even if they do not provide yield advantages under normal conditions. We also find evidence that farmers' value reduced exposure to yield losses due to severe droughts, even when this reduced exposure is not accompanied by higher average yields or even less variable yields.

We also demonstrate the importance of incorporating behavioral parameters in farmers' utility function. Incorporating these parameters in the utility function involves affecting choice probabilities. We find that more risk-averse and more loss-averse farmers are more likely to choose DT seeds over the varieties they had cultivated in previous seasons. We also find that in addition to conditioning choice probabilities, incorporating these parameters affects the valuation of seed attributes. When we control for preferences toward risk and potential losses, we find that farmers' valuations of the various DT yield distributions increase. Although the valuations for these attributes increase, there are not significant changes in the valuations for the other attributes, such as duration, seed rate, and seed reusability.

Our results suggest that there are different demand structures for DT varieties developed by the public sector and DT hybrids developed by the private sector. Although there is, on average, significant disutility associated with having to buy new seed every year (a key characteristic of hybrids), the additional yield conferred by heterosis (or hybrid vigor) results is such that many farmers would be willing to pay a significant price for a DT hybrid. At the same time, because there is such wide variation in the utility associated with purchasing new seeds every year, demand for DT hybrids is heterogeneous and therefore inelastic. Demand for DT varieties is much more elastic, but the average WTP is significantly lower than for DT hybrids. This is an important result, as it suggests natural market segmentation, implying that both DT hybrids and DT varieties could coexist in the DT rice market. Given limited research budgets and conflicting research priorities, this natural market segmentation provides opportunities for cooperation between public- and private-sector research, resulting in potentially beneficial public-private partnerships in the development and delivery of DT technologies that could benefit large numbers of poor, vulnerable farmers in India's drought-prone areas.

Although this study focuses on DT rice in the Indian state of Bihar, we provide a methodological toolkit to motivate similar studies that address abiotic stresses characterized by similar patterns of occurrence and learning among farmers. This approach could be used to explore demand for tolerance traits addressing other abiotic stresses such as submergence, salinity, excessive heat, and excessive cold; within other staples such as maize or wheat; or within other nonstaple crops such as vegetables or other horticultural crops.

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