Farmer’s Preferences for Abiotic Stress Tolerant Rice Seeds in India: Evidence from Odisha.

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Abstract:

Abiotic stresses such as droughts and floods significantly constrain rice production in India. New stress-tolerant technologies have the potential to reduce yield variability and help insulate farmers from the risks posed by these hazards. This study aims at understanding seed attributes that are important for farmers, and explores socio-economic factors behind varietal selection. Using discrete choice experiments conducted in rural Odisha, we estimate farmers' valuation for drought-tolerant (DT) and submergence-tolerant (SubT) traits embodied in paddy cultivars. We find farmers value both yield increasing traits and variability reducing traits. Interestingly, we find exceptionally high willingness to pay for short duration varieties. We also attempt to capture heterogeneity in preferences. Our results show that farmers in both drought-prone as well as submergence-prone regions value reduction in yield variability offered by cultivars. Further these valuations are higher for higher income farmers, and farmers belonging to upper (non-scheduled) castes. In addition, we used some post estimation conditioning approaches to better analyze the data and account for attribute non-attendance by farmers in choice sets and derive demand curves for hypothetical bundles of rice seeds.

Key Words: Abiotic stress, rice seeds, choice experiment, India.

JEL Classification: Q16, Q51.

1. Introduction

Abiotic stresses such as drought and submergence significantly constrain rice production in India. Of the over 40 million hectares of harvested rice area, only 45 percent is irrigated, leaving the remaining susceptible to drought. Out of the total 20.7 million hectare of rain fed rice area reported in India around 13.6 million hectare is prone to damage from droughts. Extreme drought may lead to significant income and consumption losses for the rice-growing farmers that could increase incidence of poverty. The value of rice production lost in drought years has been estimated to be as high as 36 percent of the total value of rice production in eastern India. The economic costs of droughts to rainfed rice farmers in eastern India are of the order of several 100 million dollars per year (Pandey *et al.*, 2012).

In addition about 49.81 million hectare of land area (15.2 percent of total geographic area) is prone to floods in India and on an average 10-12 million hectare is actually affected by floods every year causing a range of losses to human life, property, forests and crop damages (National Rainfed Area Authority, 2013). The flood-prone rice lands in India account for 50 per cent of the total flood-prone rice lands of the world. Out of about 3 million hectares of flood-prone rice lands of India, Eastern India accounts for 2.4

million hectares (Samal and Pandey, 2005). Approximately 60% of the Kharif season (wet season) rice production during 2010-2011 took place in the particularly flood-prone states of Andhra Pradesh, Bihar, Odisha, Uttar Pradesh, and West Bengal (Dar *et al.,* 2013). Rice production in Odisha is marked by low productivity and wide fluctuations in output due to various abiotic and biotic stresses. It has been recorded that droughts and floods occur almost in the same year or every alternate year in Odisha (Reserve Bank of India, 1984). The state has been severely affected by five major floods in the last fifteen years, including one following the devastating cyclone Paradip in 1999, as well as heavy floods in 2001, 2003 and 2006 (Rodriguez-Llanes *et al.* 2011). In a recent article in Times of India dated 18th August, 2014 it is cited that: "Due to non-availability of flood-tolerant paddy seeds, farmers of flood-hit villages in Odisha suffer huge loss of crops every year."

Climate change is likely to increase frequency of extreme weather events around the globe. During the last 15 years, the intensity and frequency of floods has risen rapidly and this trend is expected to continue as a consequence of climate change (IPCC, 2014). According to the latest report on Intergovernmental Panel on Climate Change, in the Asian Monsoon region and other tropical regions, there would be more flooding due to climate change. Coastal flood damages are expected to increase significantly during the 21st century as sea levels rise and socioeconomic development increases (Hinkel *et al.*, 2014).

Sea level rise throughout the 21st century (as a result of climate change and rising global mean temperatures) will mean that coastal and other low-lying areas throughout the world will be increasingly at risk of inundations, and, without substantial adaptation, hundreds of millions of people will be affected. At the same time, evidence suggest droughts are becoming longer, harder and more frequent. It has been predicted that in the coming years the water deficit would deteriorate further and the frequency of drought would become worse due to climate change (Bates *et al.,* 2008). In the presence of the above constraints and the potential impacts of climate change, improved rice varieties that are better able to withstand drought and submergence are likely to be effective in reducing yield and income losses for rice farmers.

Substantial scientific effort has been undertaken at breeding stress tolerant traits into staple crops. In recent years drought-tolerance (DT) globally has received a huge amount of attention from governments and foreign donors concerned about global warming and poor people who live in drought-prone regions. Expenditure on DT research has increased exponentially since 2000 (Pray and Nagarajan, 2014). Lybbert and Bell (2010) mention that since 2000 DT research in all crops easily surpassed $1 billion. From 1984 – 2002, DT was also one of the goals of the Rockefeller Foundation's International Program on Rice Biotechnology (IPRB). Between 2000 and 2005, the Rockefeller Foundation invested approximately $12 million in DT rice research and diffusion in Asia.

Many public and private sector institutes such as the International Rice Research Institute, the Central Rice Research Institute in Cuttack, Tamil Nadu Agricultural University, Mahyco, Bayer Bioscience, Dupont, Pioneer India Ltd, etc. are engaged in rice biotechnology research. Advances in biotechnology have enabled breeders to reduce farmers' exposure to risk due to droughts and floods. The new rice seeds that have increased tolerance to drought (DT) and submergence (SubT) have the potential to benefit the areas that did not benefit from Green Revolution technologies.

Several recent studies have documented potential benefits from the adoption of stress tolerant rice seeds. Mottaleb *et al.* (2012) estimates that successful development and delivery of DT varieties will produce significant benefits across South Asia, well in excess of the investment necessary to develop the technology. Ward *et al.* (2014) found that farmers in drought-prone areas of Bihar, India largely preferred DT cultivars over status quo varieties, and that farmers' degree of risk aversion and loss aversion increased this preference. Through a randomized field experiment in Odisha, Dar *et al.* (2013) studied the effects of a SubT rice varietySub1Swarna-Sub1 on rice yields, finding that Swarna-Sub1 had a significant and positive effect on rice yields (relative to non-tolerant varieties) when fields were submerged for as long as 7-14 days. They also note that low lying areas prone to floods tend to have heavy concentrations of lower caste farmers, and suggest that submergence-tolerant rice can deliver both efficiency gains (through reduced yield variability and higher expected yields) as well as equity gains (disproportionately benefitting some of the most marginal groups of farmers).

The development and delivery of stress-tolerant traits has been seen as a potential avenue through which human livelihoods can be at least partially insulated from the negative impacts of these stresses. But the successful development of these technologies does not imply that the benefits will necessarily be realized; realization of these benefits is contingent upon farmers actually cultivating the seeds in which these technologies are embodied. Among many resource-poor farmers, reliance upon saved seed (rather than newly purchased seed) necessarily limits their access to these new technologies and the benefits they confer. Furthermore, unlike some biotic stress-tolerant seeds (such as insect-resistant crops containing the soil bacterium B. thuringiensis—or Bt—in their DNA), the relative benefits of abiotic stress-tolerant cultivars are largely non-monotonic. While the benefits of stress-tolerant cultivars are increasing for some range of stress severity, they are decreasing for some range of stress severity, and likely zero once the stress level becomes too severe (Lybbert and Bell, 2010). Additionally, under normal conditions the stress-tolerant cultivar may underperform popular non-tolerant varieties. The non-monotonic nature of these relative benefits makes it difficult for farmers to learn about the benefits of the technology, which may hinder their widespread adoption, even where we might objectively expect positive impacts from adoption. In a field experiment conducted in Odisha, India, Emerick (2013) reports that despite the fact that 84 percent of the farmers are expected to gain from cultivating Swarna-Sub1, only 40 percent of farmers adopted the technology when seeds were sold door-to-door. For the successful diffusion of new agricultural technologies like abiotic stress-tolerant seeds, it is important for researchers, breeders, policymakers and development practitioners to have a deeper understanding of farmers' preferences for crop attributes.

This study aims to fill this gap. The study has a two-fold objective. The first objective is to quantify farmers' valuations for various rice seed attributes using discrete choice experiments, particularly focusing on farmers' valuation for DT and SubT traits. The results would be useful not only for researchers developing these new technologies, but also in guiding public and private sector investment in the development and delivery of such technologies. While the rice seed system in India is presently dominated by public research institutions (e.g., state agricultural universities, the Indian Council of Agricultural Research, ICAR, etc.), there is a growing presence of private sector seed companies, particularly in developing rice hybrids. While the present study is primarily concerned with the development of stress-tolerant inbred varieties, Ward *et al.* (2014) have shown that the demand structures for DT hybrids is distinct from that of DT varieties, which may suggest natural market segmentation and the potential for the non-competitive coexistence of DT hybrids and varieties. They suggest that this scenario may provide the basis for public-private partnerships to develop stress-tolerant traits that can be embodied in these different genomic backgrounds. The second objective is to investigate the driving socioeconomic and behavioral forces behind varietal selection. This would contribute to the literature on adoption of agricultural technologies by understanding which sections of the society may have low willingness-to-pay for new technologies and therefore, may require some form of external intervention (e.g., targeted subsidies, vouchers, etc.) to incentivize uptake. This could guide required policy intervention for wider adoption of new technologies.

We find that farmers value yield-increasing as well as risk-reducing attributes. The valuation for DT traits dominates that of SubT traits. There is considerable heterogeneity in these valuations across farmers. We explore socio-economic factors driving this heterogeneity, finding income to be an important determinant of these valuations. Farmers having higher income are willing to pay more for yield-increasing and risk -reducing traits.

The rest of the paper is organized as follows. The next section describes the discrete choice model and the empirical methodology used. Section 3 describes the characteristics of the study sites and sampling considerations as well as summary statistics of the households. Estimation results are reported in Section 4. Section 5 discusses the socio-economic forces underlying heterogeneous preferences and section 6 analysis attribute non-attendance. Finally Section 7 derives the demand curves and the last section contains the conclusions.

2. Empirical Methodology

The study relies upon the use of discrete choice experiments to estimate farmers' valuation for different seed traits. In a choice experiment, individuals are presented a series of hypothetical choice scenarios in which they must choose between bundles of different traits, each taking one of a number of pre-specified levels. Through statistical analysis of participants' choices given the alternatives available in each choice scenario, the researcher is able to estimate marginal values (in either utility or monetary terms) for the various attributes embodied in the alternatives. Researchers control the experimental choice environment by providing necessary variation in attribute levels, which may not be present in the historical data. The methodology is particularly useful for getting valuation of products that are yet not in the market, for instance, new technologies that are at the development stage.

Choice experiments have been widely used for studying a wide variety of topics in a wide range of disciplines, including marketing research, transportation, and economics. Within the agricultural and resource economics literature, this methodology has been employed to analyze consumer preferences for environmental amenities (Selassie and Kountouris, 2006; Bennet and Blamey, 2001; Wang et al., 2008; Bell et al., 2014), ecosystem services (Hurd 2006; Villalobos 2010), food quality attributes (e.g., Lusk and Schroeder, 2004), and new and improved production technologies (e.g., Ward et al. 2014). The use of choice experiments in India is relatively rare to date. Most stated choice studies in India have used the traditional contingent valuation approach for the valuation of new agricultural technologies (Krishna and Qaim 2006; Kolady and Lesser 2006).

A concern with stated–preference experiments is the validity of the results since respondents make choices in a hypothetical setting without actual financial recourse for their choices. In such hypothetical settings, respondents may not answer in such a way that truly reflects choices that would be made in real market situations, so valuations elicited through such experiments may be biased upward. Carson *et al.* (2003) identified several conditions under which respondents can be expected to answer honestly. An important condition is 'consequentiality', the condition in which respondents believe that choices have some consequence, or affect some outcome that matters to the respondent. For our study, each respondent was informed that the results from the study would provide information to researchers engaged in developing improved varieties and would also potentially inform public and private sector investment in the discovery, development, and delivery of stress tolerant technologies. Another important condition is that respondents are able to relate to the options that are presented. In this regard, the choice scenarios with which participants are presented should closely resemble real-world seed purchasing decisions they face on a regular basis. In an attempt to satisfy this condition, the seed attributes and their respective levels specified in our experiment were carefully chosen so that farmers could relate to them. Prior to designing the choice experiment, we conducted a number of focus group discussions (FGDs) with farmers in Cuttack district of Odisha to identify the attributes that are important for the farmers. We also consulted the existing literature and met with rice scientists at the Central Rice Research Institute of India (CRRI) to decide attribute levels. We also tried to ensure that respondents could understand and meaningfully relate to the options. The choice sets and accompanying survey were translated into the local language (Oriya), and the enumerators used the local language in interviewing participants. Visual illustrations were also used for better comprehension of the alternatives.

Through the course of the FGDs, farmers identified yield to be the most important trait for selecting a rice variety. Yields, however, are the result of stochastic processes, so characterizing yields, especially in light of these abiotic stresses, requires some finesse. Dalton *et al.* (2011) used a novel approach to quantify the DT attribute in their study of Kenyan farmers' preferences for DT maize. They describe the attribute not only in terms of mean (expected) yield but also the variance of yield distribution under different moisture stress conditions. Ward *et al.* (2014) modified this approach in studying demand for DT paddy among farmers in Bihar, India. We have followed the basic approach of Ward *et al.* (2014) to quantify DT in our study. The DT attribute takes three levels related to different degrees of stochastic dominance over a popular local variety.[1] In the first of these three levels, the DT first-order stochastically dominates the reference variety: it yields higher under normal conditions, under moderate drought stress conditions, and under severe drought stress conditions. In the second level, the DT second-order stochastically dominates the reference variety: while it does not yield more (nor less) than the reference under normal conditions, it has higher yields under both moderate and severe drought stress conditions. In the third and final level, the DT third-order stochastically dominates the reference variety: the DT yields no more (nor less) than the reference variety under normal and moderate drought stress conditions, but yields more under severe drought stress. The yield distribution of Sahbhagi dhan (a recently released DT cultivar) has informed our specification of yield distributions for different levels of stochastic dominance presented in our choice experiment (Verulkar *et al.,* 2010). We include submergence tolerance as an attribute with three varying levels, namely, tolerance of 0-5 days, 5-10 days and 10-15 days of full submergence. Our reference

[1] Swarna, a popular rice variety in Odisha, that gives a yield of 53 quintals per hectar (qtl/ha) under normal condition, 22 qtl/ha under moderate drought stress and 6qtl/ha under severe drought stress (Verulkar et al, 2010) has been considered as the reference variety.

variety, Swarna, can tolerate submergence for 0-5 days and a recently released SubT rice variety, Swarna-Sub1, can tolerate submergence up to 15 days.[2]

During FGDs farmers also indicated short duration to be an important attribute. This represents another avenue through which breeding research can increase farmers' resilience to droughts, since the short duration allows farmers to escape drought (e.g., postponing transplanting in the event of delayed monsoon onset). We have included three levels of crop duration—short (less than 120 days), medium (120-135 days) and long (more than 135 days). Based on our consultation with scientists at CRRI, we find that around 90 percent of area under rice cultivation in Odisha is occupied by inbreds and only 10 percent is under hybrids. To capture farmers' preferences for inbreds, we have included an attribute that distinguishes between 'seeds that can be stored and reused in the next season' and those that cannot.[3]

Finally, since we are ultimately interested in estimating money metric measures for willingness to pay, we incorporate an additional parameter capturing prices with different levels. While the average price for rice inbreds in Odisha varies from Rs 12 to Rs 15 per kg, the average price for hybrids is around Rs 250 per kg.[4] To capture the price of inbreds as well as hybrids, and to provide enough variation in seed price levels we have included six price levels ranging from Rs 15/kg to Rs 300/kg in the choice sets. . The attributes and various levels are summarized in Table 1.

There is a vast literature exploring the many issues pertinent to choice experiment design, and many criteria by which such designs can be evaluated. Following standard practice, we constructed a D-Optimal experimental design based on a main-effects only linear utility specification with null priors. This design generated 36 unique choice sets which were subsequently randomly allocated into four blocks of 9 choice sets each.[5] Farmers were randomly allocated to each of these four blocks, with a balanced number of farmers assigned to each of the four blocks. Each choice set contained three alternative hypothetical rice seeds plus a status quo option (i.e., the rice seed they used in the past rice season). An example of a choice card is presented in **Ошибка! Источник ссылки не найден.**.

[2] In a series of field trials, Singh *et al.* (2009) found Swarna-Sub1 to withstand submergence for up to 17 days. Given likely differences in conditions between agronomic field trial plots and farmer fields, we have assumed a slightly reduced degree of tolerance.

[3] Most of the benefits that arise as a result of the hybridization process (such as increased productivity and uniformity) are fully expressed in first generation seeds, but decline dramatically in subsequent generations. Therefore, farmers must purchase new hybrid seeds every year in order to continually realize these benefits.

[4] The market price of hybrid rice is varying between Rs 200-250 per kg in India. (Rice Knowledge Management Portal) http://www.rkmp.co.in/search/node/price%20of%20hybrid%20rice.

[5] D-optimal designs minimize the D-error of the design, which is computed as the weighted determinant of the variance-covariance matrix of the design, where the weight is an exponential weight equal to the reciprocal of the number of parameters to be estimated.

The CE approach is consistent with Lancaster's theory of consumer choice (Lancaster 1966) which postulates that consumption decisions are determined by the utility that is derived from the attributes of a good, rather than from the good per se. The econometric basis of the approach rests on the framework of random utility theory, which describes discrete choices in a utility maximizing framework (Mc Fadden 1974).

Let us consider a farmer labeled *n* who faces *J* alternatives of rice seeds contained in a choice set *C*. U_{ni} is the utility that farmer *n* obtains from choosing alternative *i*. The utility that decision maker *n* obtains from alternative *j* is U_{nj} , *j=1,……,J*. The choice of a farmer is designated by a variable y_{ni} that takes a value 1 or 0. The dummy variable y_{ni} takes a value 1 only if he derives a greater utility from choosing alternative *i* as compared to all other alternatives in the choice set.

$$y_{ni} = \begin{Bmatrix} 1, if\ U_{ni} > U_{nj}, \forall j \neq i \\ 0\ \ otherwise \end{Bmatrix}$$

The utility that a farmer obtains from choosing an alternative is decomposed into a part labeled V_{ni} that is observable to the researcher (systematic component) and a part ε_{ni} that is unobservable and treated by the researcher as random (Train, 2003).

$$U_{ni} = V_{ni} + \varepsilon_{ni} \qquad (1)$$

The attributes of alternative *i* in choice occasion *t* faced by respondent *n* are collectively labeled as vector X_{nit} . The utility that respondent *n* derives from choosing alternative *i* on choice occasion *t* depends on the attributes of alternative *i* faced by farmer *n* in choice situation *t* (X_{nit}).

$$V_{nit} = \beta X_{nit} \qquad (2)$$

Putting (2) in (1), we get

$$U_{nit} = \beta X_{nit} + \varepsilon_{nit}\ \forall\ i \qquad (3)$$

where β is the vector of taste parameters mapping the attribute levels into utility, and ε_{nit} is an independently, identically distributed error term. Different choice models arise from different distributions of ε_{nit} and different treatments of β. We will assume that ε_{ni} takes an extreme value type I (Gumbel) distribution with probability density $f(\varepsilon_{ni}) = \exp[-\epsilon_{ni} - \exp(-\epsilon_{ni})]$.

We now derive the logit choice probabilities following Mc Fadden (1974).

The probability that respondent *n* chooses alternative *i* given all other alternatives in a choice set is then given by:

$$Prob(y_{nit} = 1) \equiv P_{ni} = Prob(V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt} \ \forall \ j \neq i)$$

$$= Prob(\varepsilon_{njt} < \varepsilon_{nit} + V_{nit} - V_{njt} \ \forall \ j \neq i) \qquad (4)$$

The algebraic manipulation of the cumulative distribution of (4) over all values of ε_{ni} results in a closed form expression:

$$Prob(y_{nit} = 1) \equiv P_{nit} = \frac{\exp[V_{nit}]}{\sum_j \exp[V_{njt}]} = \frac{\exp[X_{nit}\,\beta]}{\sum_j exp\,[X_{njt}\,\beta]} \qquad (5)$$

which is the basic conditional logit model and can be estimated using maximum likelihood. The conditional logit framework imposes homogeneous preferences across respondents and assumes independence of irrelevant alternatives (IIA) (Hausman and McFadden, 1984).

Because farmers are heterogeneous, their preferences over seed attributes may also be heterogeneous. Within the discrete choice literature, there are several ways for accounting for preference heterogeneity. A common method of evaluating preference heterogeneity is estimation of random parameters logit (RPL) models, also called mixed logit. The RPL 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 *n* chooses alternative *i* from the choice set *C* in situation *t* is given by

$$P_{ijt} = \int \frac{\exp[\beta_n X_{nit}]}{\sum_j \exp[\beta_n X_{njt}]} f(\beta_n|\theta) d\beta_n \qquad (6)$$

Under RPL, the coefficient vector β representing individual tastes, is unobserved and varies randomly in the population with density denoted $f(\beta_n|\theta)$, where θ represents the parameters of this distribution. the matrix θ defines the parameters characterizing the distribution of the random parameters, the family (e.g., normal, lognormal, triangular, etc.) of which is specified by the researcher. For our purposes, we allow the coefficients corresponding to all attributes except price to vary normally, while the price coefficient is fixed.

Once the parameter estimates are obtained by application of the most appropriate model, implicit prices of various attributes can be derived in the form of marginal willingness to pay (WTP) for each attribute.

The K vector of parameters $\beta = (\beta_1, \beta_{2,\ldots\ldots\ldots}\ \beta_k)$ defining tastes and preferences over the K attributes, can be interpreted as marginal utilities and the ratio of two such marginal utilities is the marginal rate of substitution of one for the other. If one of the included attributes (say the p^{th} attribute, is the price of the alternative, then the indirect utility V_i can be represented as:

$$V_i = \sum_K \beta_k x_k + \beta_p p \qquad \text{(7) [From equation 2]}$$

Where β_p is the parameter of the monetary attribute for *nth* individual, alternative *i* and choice occasion *t* and can be interpreted as marginal utility of money and *p* denotes the price. If this equation is subject to total differentiation, and keeping the utility level unchanged (dv = 0), the marginal WTP for a unit increase of attribute x_k , keeping all other attributes constant can be defined as follows:

By total differentiation of equation (7), we get

$$MWTP_{x_k} = \frac{dp}{dx_k} = -\left(\frac{\partial v}{\partial x_k}\right) \Big/ \left(\frac{\partial v}{\partial p}\right) = -\frac{\beta_k}{\beta_p} \qquad (8)$$

Where β_k is the estimated parameter for the k^{th} attribute. The ratio of coefficients represent the marginal rate of substitution between price and the rice seed attribute in question, or the marginal willingness to pay measure (WTP) for a change in any of the attributes. The marginal utility of price is assumed to be negative, while the marginal utility of favorable attributes will be positive, thus, a negative of this ratio implies that the WTP for a favourable attribute is represented as a positive sum.

3. Data sources

The experiments and accompanying survey were conducted with farmers in three different districts of Odisha in June-July 2013. Odisha is one of the largest rice producing and consuming state in India. It is also considered as a centre of origin of rice and holds rich biodiversity in rice (Arunachalam et al., 2006). The state lies in eastern India and shares its coastline with Bay of Bengal. The topography of Odisha is such that it contains both low-lying coastal areas, which frequently get flooded for prolonged periods, and rainfed uplands that suffer from moisture stress due to variability in rainfall. The plateau region comprises about 77 percent of the total geographical area and the remaining 23 percent is the coastal region. A majority of the cultivated land in Odisha (about 65 percent) is rainfed. Paddy is a dominant crop and constitutes 90 percent of total food grain production. Agricultural production in Odisha has suffered from frequent droughts and floods. The districts included in the study have been carefully chosen to include both areas that suffer from droughts as well as prolonged floods.

We used a multi-stage sampling approach to select our survey sample. In the first stage, we have identified three adjacent districts in Odisha that are susceptible to drought and/or floods: specifically, we identified the districts Dhenkanal, Cuttack and Jagatsinghpur (**Ошибка! Источник ссылки не найден.**). The district of Dhenkanal has been repeatedly affected by droughts, including recent years, 2002, 2005, 2006, 2008 and 2010. During 2008, it was estimated that more than 70 percent of total rice area in Dhenkanal was adversely affected due to drought (Behura, 2008). Dhenkanal is also one of the eight districts in Odisha identified by the Government of India (GOI) for treatment under the Drought-Prone Area Programme (DPAP). Jagatsinghpur district, situated along the Bay of Bengal on the eastern coast of Odisha, is prone to various natural hazards such as floods and cyclones. The district has been severely affected by five major floods in the last fifteen years. The third district Cuttack demonstrates a great deal of heterogeneity in terms of agro-climatic conditions, with some areas susceptible to droughts and others susceptible to floods.

In the second stage we stratified blocks (sub-district administrative units) within Cuttack and Dhenkanal that were being affected by droughts. The drought-affected blocks drawn for the study is directly proportional to the population of that block as a proportion of total population of all the drought-affected blocks within Cuttack and Dhenkanal. Similarly, we stratified blocks amongst flood-affected regions of Cuttack and Jagatsinghpur. This way, we identified four blocks affected by droughts—namely Kankadahad (Dhenkanal), Parajang (Dhenkanal), Tangi (Cuttack) and Athagad (Cuttack)--and four blocks affected by floods--namely Banki (Cuttack), Tirtol (Jagatsinghpur), Kujang (Jagatsinghpur) and Jagatsinghpur block (Jagatshinghpur). Hereafter we'll refer to these regions as drought-prone and flood-prone, respectively. We then randomly selected two villages from each of these eight blocks. We used probability proportional to size sampling to select these villages. Finally, we randomly selected 25 rice growing households in each village from household lists provided by village leaders. The resulting total sample size is 400 rice-growing households.

Descriptive statistics of the sampled farmers are reported in **Ошибка! Источник ссылки не найден.**. While the second column presents the characteristics of the households in the pooled sample, the third and fourth columns present and compare the characteristics of farmers in the drought-prone and submergence-prone regions separately. Out of the total of 100 scheduled-caste (SC) households, 67 are located in the submergence-prone areas whereas almost all (30 of 31) scheduled-tribe (ST) households in our sample are located in the drought-prone region. Tribal populations in India tend to reside in the upland/hilly regions, so it is not surprising to find nearly all ST households in our sample located in the drought-prone upland region. This sample characteristic is consistent with Dar *et al.* (2013) who suggest that years of discrimination and marginalization have led to ST households largely located in dry areas and SC households largely located in flood-prone areas.

In our sample, as compared to the households in the drought-prone region, the households in submergence-prone areas have higher mean annual income, are more educated on average, and have a higher proportion belonging to the general caste.

4. Estimation and Interpretation of Results

We first report results from the random parameter logit model using the pooled sample of 400 respondents in **Ошибка! Источник ссылки не найден.**. These initial results are from a fully compensatory model, which assumes that all respondents attend to all presented attributes. Further, we examine how the valuations for various rice seed attributes differ across farmers in drought-prone and submergence-prone regions. For this purpose, we stratified our sample across the two regions and ran separate choice regressions across the drought prone and submergence prone regions. Each region has a sample size of 200 households.

The utility parameters for all rice seed attributes (except price) were entered as random parameters assuming a normal distribution. The results provide both the posterior mean and standard deviations for the random willingness to pay parameters. While the posterior mean values of attributes provide us valuable information on the relative value associated with each of the attribute levels the latter gives information regarding the shape of the parameter distributions.

Before interpreting the results, we discuss the impact of scale parameter on the coefficients of marginal utility for various attributes in rice seeds. As discussed in the methodology section in the previous section, utility that farmer *n* obtains from choosing an alternative *i* is given by: $U_{ni}^{*} = V_{ni} + {\varepsilon_{ni}}^{*}$, where the unobserved portion(${\varepsilon_{ni}}^{*}$) has variance $\sigma^2 * \pi^2/6$.

Variance is any number re-expressed as a multiple of $\pi^2/6$. Since, the scale of utility is irrelevant to behavior, utility can be divided by σ without changing behavior. Utility becomes $U_{ni} = V_{ni}/\sigma + \epsilon_{ni}$ where $\epsilon_{ni} = \epsilon_{ni}^{*}/\sigma$, ϵ_{ni}^{*} are the original error terms and the choice probability is given by:

$$P_{nit} = \frac{\exp[V_{nit}/\sigma]}{\sum_j \exp[V_{njt}/\sigma]} = \frac{\exp[X_{nit}(\beta^*/\sigma)]}{\sum_j \exp[X_{njt}(\beta^*/\sigma)]} \qquad (9)$$

Thus, each of the coefficient is scaled by 1/σ. The parameter σ is called the scale parameter, because it scales the coefficients to reflect the variance of the unobserved portion of utility. Our model is expressed in its scaled form with $\beta = \beta^{*}/\sigma$ and it estimates the parameters β, but for interpretation it is important to note that these estimated parameters are actually estimates of original coefficients β^{*} divided by the scale parameter σ. Therefore, the marginal utility coefficients that are estimated indicate the effect of each observed variable relative to the variance of unobserved factors.

However, the scale parameter does not affect the ratio of any two coefficients, since it drops out of the ratio ($\beta_1/\beta_2 = (\beta_1^{*}/\sigma)/(\beta_2^{*}/\sigma)$=$\beta_1^{*}/\beta_2^{*}$ where the subscripts refer to the first and second coefficients. Thus, WTP measures of the marginal rate of substitution are not affected by the scale parameter. Only the interpretation of magnitude of all coefficients is affected. Thus, although marginal utility coefficients cannot be directly compared across drought prone and submergence prone regions, WTP estimates can be compared.

We are interpreting the results for the pooled sample as well as subsamples (drought prone and submergence prone). It is possible that the variance of the unobserved factors is different across the drought prone and submergence prone regions. Thus, in order to compare the valuation of farmers across the two sub groups, we use WTP estimates rather than marginal utility coefficients as they are independent of scale effects. However, the pooled sample results can be interpreted from the marginal utility coefficients by assuming that the variance of the unobserved factors are the same for all individuals.

Column 2 in table 3 depicts the maximum likelihood estimates for the RPL model for a pooled sample of 400 households with 3600 choices, while columns 3 and 4 shows the results from separate regression on 200 households each from drought prone and submergence prone blocks respectively.

The utility parameters for all rice seed attributes (except price) were entered as random parameters assuming a normal distribution. However, the marginal utility of price is treated as non-random. The results provide both the mean values for the marginal utility parameters as well as standard deviation for the normally distributed parameters. While the mean values of attributes provide us valuable information on the relative value associated with each of the attribute levels the latter gives information regarding the shape of the parameter distributions. In addition it also elicits willingness to pay measures for the pooled sample which is depicted in table 3.1 along with confidence intervals.

The mean marginal utilities of almost all the attributes (except medium duration and submergence tolerance 10-15 days) are statistically significant at one percent level and with the expected signs (Table 3, column 2, upper panel). The negative coefficient of marginal utility associated with seed price suggests that farmers would prefer cheaper seeds to more expensive seeds.

There are positive mean marginal utilities and high willingness to pay for each of the yield distribution attribute levels. The marginal utility of a SSD distribution is higher than that of FSD distribution which in turn is higher than that of a TSD distribution. However, the difference between the mean values of FSD and SSD is not statistically different from each other (t test). Farmers are willing to pay as high as Rs 400 (approximately) for a FSD yield distribution and Rs 417 and Rs 378 for a SSD and TSD yield distribution, respectively. As discussed previously that FSD and SSD distribution gives higher yields under all states of nature whereas a TSD distribution depicts reduction in yield variability offered by rice cultivars. Thus, a high WTP for FSD and SSD as compared to TSD implies that farmers prefer higher expected yields over and above lower yield variability and protection against severe downside risk. The RPL model results also depict that farmers prefer short duration rice cultivars as compared to medium and long duration. They are willing to pay as high as Rs 231 for short duration rice seeds (Table 3.1). This could be because short duration provides a means of escaping the abiotic stress---drought or flood. Moreover, besides paddy, various other crops such as groundnut, pulses, Moong, Biri etc are grown in Odisha. Thus, short duration may allow farmers to grow these other crops which could enhance their farm incomes. Moreover, farmers assign negative marginal utilities if seed cannot be stored and reused in the next season and are willing to pay Rs 229 for this characteristic. Farmers in our pooled sample do not value submergence tolerance (10-15 days) attribute but they value submergence tolerance (5-10 days) and willing to pay Rs 84 for it. Our results depict that farmers in Odisha on an average, have a higher valuation for drought tolerant attributes as compared to submergence tolerance attributes.

There is substantial heterogeneity in farmer's valuation for almost all rice seed attributes, as evidenced by statistically significant standard deviations (Lower panel, column 2, table 3). The highest degree of heterogeneity is seen in short duration followed by medium duration, seed reusability and submergence tolerance (10-15 days) attribute.

Comparing the valuation of farmers across the drought prone and submergence prone regions using willingness to pay estimates (Table 3.2 and 3.3), we find that farmers in submergence prone areas have a higher valuation for almost all attributes (except for grain cannot be saved and SubT 5-10 days attribute) as compared to their counterparts in drought prone areas. It could be because these farmers have higher incomes, better education and a greater proportion of individuals belong to general caste groups (as evidenced through summary statistics of households in our sample). The high WTP for short duration varieties by farmers from submergence prone areas could be because farmers in our sample are exposed to frequent flood which washes away the rice plant. Thus, by growing short duration varieties the extent of loss gets reduced as farmers could quickly escape floods. Moreover, as expected, farmers in submergence prone areas have a positive and significant valuation for both submergence tolerance 5-10 days and 10-15 days attribute. They are willing to pay Rs 74 and Rs 86 for the two attributes respectively. However, farmers in drought prone regions have a negative and insignificant valuation for submergence tolerance 10-15 days attribute. Also, there is considerable heterogeneity seen in the valuation of almost all the attributes across the two regions as evidenced through standard deviation measures.

5. Socio-economic forces underlying heterogeneous preferences

The presence of considerable heterogeneity in the preferences of farmers for various attributes for both the pooled sample as well as subsamples motivates us to understand the sources of such heterogeneity and in turn led us to look for some specific household characteristics like income, caste, etc., for explaining such behavior. In order to identify the possible sources of observed heterogeneity, interactions of household specific social and economic characteristics with choice specific attributes are included in the utility function. More specifically, we estimated two different RPL models: one in which rice seed attributes were interacted with an economic attribute namely income of the household and second, where rice seed attributes were interacted with caste of the households[6].

***Rice seed attributes interaction with Income*:** We compute the median value of income of farmers in our sample and introduced two dummy variables namely low income (which takes a value 0 for income less than median income and 1 otherwise) and high income (which takes a value 1 for income greater than median income and 0 otherwise). These dummy variables were interacted with marginal utilities of various attributes for the pooled sample. Finally the WTP of farmers belonging to different economic groups is compared. The RPL model results are depicted in table 4.

Table 4 depicts the marginal utility of all rice seed attributes interacted with the dummies for high income and low income groups. Column 3 in table 4 depicts and compares the WTP estimates for both the low income and high income groups along with their confidence intervals.

[6] We do recognize that income and caste could have potentially confounded effects but we cannot isolate the effects of income from that of caste in separate regressions.

Both the low income and the high income group of farmers have a statistically significant marginal utility coefficient for the three (FSD, SSD and TSD) yield distributions. While the farmers belonging to high income groups have a higher valuation for yield enhancing attribute (FSD), the low income groups have a higher valuation for yield variability reducing attribute (SSD and TSD).

Comparing the valuation of farmers in both the income groups for submergence tolerance traits, we find that high income farmers have a higher and significant valuation for these attributes (Rs 132 and Rs 88) as compared to low income groups. Similarly, high income classes have a higher willingness to pay for short duration and medium duration attribute as compared to their counterparts. Thus, income differences could account for significant heterogeneity in our sample.

2. Rice seed attributes interaction with Caste: We also tried to investigate if caste differences in our sample could explain the heterogeneity in the preferences of farmers or not. For this purpose, we tried interaction of caste dummies with various rice seed attributes. We include two caste dummies namely non-scheduled groups (Non SCST) including both the general as well as other backward classes (taking a value 1 if belonging to this group) and 0 otherwise, and the scheduled groups (SCST) taking a value 1 if belonging to SC and ST caste and 0 otherwise. These two caste dummies were interacted with rice seed attributes in the pooled sample and the corresponding willingness to pay is estimated. The results are listed in table 5.

Indeed there exists considerable variation in the valuation of different caste group of farmers for various rice seed attributes. The non-scheduled (Non SCST) groups have a significantly higher valuation for both the yield increasing and yield variability reducing attributes as compared to scheduled caste groups. Similarly, the WTP of Non-SCST farmer's for submergence tolerance (5-10 days), seed reusability and short duration attributes is higher than the scheduled caste groups. Thus, farmers belonging to non-scheduled groups have a higher valuation for all rice seed attributes.

These results show that different group of farmers have a different valuation for various rice seed attributes. While the higher income groups have a higher valuation for yield enhancing, submergence tolerance and short duration attributes, the lower income groups have a higher valuation for SSD, TSD and seed reusability attributes. Contrary to this, the non-scheduled groups have a higher valuation for almost all rice seed attributes as compared to the scheduled caste groups. This is because farmers belonging to lower caste groups have a higher marginal utility of price. The result are interesting and suggests that new and improved agricultural crop technologies such as DT and SubT rice seeds are highly valued by farmers in Odisha. But different income and caste groups have a different valuation for such technologies. Thus, it informs the policy makers to undertake appropriate measures in the equitable distribution of such seeds across the various socio-economic groups of farmers.

6. Attribute Non-attendance

It has been argued in the literature that some respondents may simplify the choice sets by ignoring one or more attributes describing the alternatives. Information on this is elicited from the respondents in the form of direct questions on attribute attendance and non-attendance after the completion of their responses on choice sets (Hensher, 2008; Scarpa et al., 2009). While these direct questions put to respondents may help identifying that part of the sample population which consistently ignore certain attributes across choice sets, it is not clear whether researchers should rely on this information during model estimation. For example, a respondent may indicate that he/she ignored a certain attribute whereas in reality they would have given a lower level of importance to it as compared to other attributes. Moreover, the ignoring may only apply to a subset of choice situations. Thus, rather than relying on stated preference approaches, Hess and Hensher (2010) attempted to infer such information from the data by making use of post estimation conditioning approaches. We follow their approach in identifying attributes that farmers are not paying attention to. For this purpose individual coefficients need to be estimated by conditioning the posterior mean marginal utility estimates on observed choices and choice experiment data. We now describe the methodology used to derive individual level coefficients, and then how these coefficients are used to identify attribute non-attendance. We re-estimate constrained RPL model incorporating attribute non-attendance. The RPL model allows random taste heterogeneity by allowing marginal utility coefficients (β vector) to be distributed randomly across respondents in the sample population. The estimated parameters describe the distribution of β in the entire sample but do not provide any information on the likely location of a given individual on this distribution. One could obtain more information on individual β coefficient by conditioning on the observed choices for specific individuals. This involves a distinction to be made between the distribution of β in the population (unconditional distribution) and the distribution of β in the subpopulation of people who faced the same alternatives and made the same choices, yielding the conditional distribution.

We had earlier assumed the unconditional distribution, i.e., distribution of β to be normal and estimated and interpreted the unconditional RPL model results in section 4. Now, we derive the conditional distribution of marginal utilities for each of the attributes and estimate the mean and standard deviation for each attribute of the 400 individuals in the sample.

Let y_n denote the sequence of observed choices for respondent n, then the expected value of β conditional on a given response pattern y_n and a set of alternatives characterised by x_n is given by[7]:

$$E[\beta|y_n, x_n] = \frac{\int \beta [\prod_{t=1}^{T} \prod_{j=1}^{J} P_{nit\,|\beta}]^{y_{nit}} f(\beta|\theta) d\beta}{\int [\prod_{t=1}^{T} \prod_{j=1}^{J} P_{nit\,|\beta}]^{y_{nit}} f(\beta|\theta) d\beta} \quad (10)$$

Intuitively this can be thought of as the conditional mean of the coefficient distribution for the sub-group of individuals who face the same alternatives and make the same choices. This way we can obtain estimates of the conditional distribution of β for each respondent.

To identify attributes ignored/irrelevant for farmers, we compute the coefficient of variation (CV, also referred to as the noise-to-signal ratio, or the ratio of the standard deviation to the mean) of the conditional distribution for each attribute level for all the 400 households (Hess and Hensher, 2010). If the CV is greater than a certain threshold level for a particular individual, then it suggests that an individual is ignoring that particular attribute in his decision making process. A high coefficient of variation implies that the variation in stated preferences are excessive relative to the mean, which makes the distribution "noisy." A summary of the number of households with coefficient of variation greater than or equal to 2.5 for each attribute is contained in Table 6.

Following standard practice, we consider that farmers whose CV for a particular attribute exceeds 2.5[8] ignored that attribute when evaluating the choice sets they faced. Table 6 shows that the attributes most often ignored in the pooled sample are submergence tolerance for 5-10 days, submergence tolerance for 10-15 days followed by medium duration.

Given that a considerable number of households ignored certain attributes, we re-estimate the RPL model by specifying the coefficient of marginal utility to be zero for ignored attributes in households' utility functions. The results of this constrained RPL model are presented in table 7, while the distribution of marginal WTP are reported in **Ошибка! Источник ссылки не найден.**.1.

[7] For complete derivation of conditional parameters, refer chapter 11, Train (2003).

[8] In this analysis, we worked with different threshold level scenarios. We compute the number of households with coefficient of variation greater than 2, 2.5 and 3 for various attributes. But we present the results for the case where CV is greater than 2.5 as the constrained RPL estimated for this case represented the best fit in terms of log-likelihood.

We find that qualitatively the results for the marginal valuation of attributes associated with DT technology (i.e., the three yield distributions), short duration, and having to purchase new seed every year are similar to those obtained in the unconstrained (or total attribute attendance) model. Although the submergence tolerance 10-15 days and medium duration attribute are still insignificant in the constrained RPL model but the valuation for submergence tolerance 5-10 days, short duration and seed reusability has increased as compared to the unconstrained model (total attribute attendance). Also, there is lesser degree of heterogeneity in farmer's preferences for various attributes as evidenced from a lower standard deviation estimates for almost all attributes as compared to the unconstrained model.

Comparing the willingness to pay estimates across the two regions, we find that now farmers in submergence prone regions are willing to pay as high as Rs 180 for submergence tolerance (5-10 days) attribute as compared to Rs 74 in the unconstrained model (Table 8.1and 8.2). Moreover, their valuation for this attribute is higher than their counterparts in drought prone regions. Farmers in submergence prone areas have a higher valuation for almost all attributes (except grains cannot be saved and reused) as compared to drought prone areas. Also, farmers in submergence prone areas have a positive and significant valuation for submergence tolerance 10-15 days attribute whereas their counterparts in drought prone areas have an insignificant valuation for this attribute. Hence, the analysis on the estimates of conditional distribution of individual level coefficients, re-estimation of RPL model after factoring out attribute non-attendance, gives a better insight about the valuation of attributes considered/ignored by farmers in choosing a particular alternative rice seed.

7. Demand Curves

In addition to estimating the constrained RPL model, the conditional parameter distributions obtained from constrained RPL model were also utilized to compute the individual willingness to pay measures for each of the attributes.

We can sum WTP estimates for a bundle of attributes and compute an approximate value of how much farmers would be willing to pay for a particular seed containing that combination of attributes. For e.g., it might be interesting to determine how much farmers would be willing to pay for a short duration drought tolerant (DT) seed that can be reused which yields 53, 32 and 16 under normal, moderate and severe drought stress conditions (SSD). For this purpose, we would simply add the WTP for the SSD, short duration and seed reusability attributes that are embodied in this hypothetical bundle of rice seed. Each individual has a unique WTP for this bundle of hypothetical seed. Thus, we plot the percent of farmers who are willing to pay different prices for this bundle and derive the demand curves for a hypothetical seed with specified attributes. Similarly, we estimate the demand curve for submergence tolerant (SubT) medium duration seed that can be reused as well as can't be reused. We also derive the demand curve of another hypothetical bundle which incorporates a super seed which is a combination of both DT and SubT seed that can't be reused. The various demand curves are depicted in figure3. The alternative demand curves are downward sloping suggesting that at higher prices, demand is lower.

The figures depict demand curves for seeds having attributes associated with drought tolerance and seeds having attributes associated with submergence tolerance. There exists a positive and high demand for seeds for various hypothetical bundles. The demand for seeds with drought tolerant attributes (eg. SSD, short, seed can be reused) is higher than the demand for seed with submergence tolerance attribute (subT, medium, seed can be reused). Moreover, demand for DT seed that can be reused (SSD, short, reused) is higher than the demand for DT seed that cannot be reused. Similarly, demand for SubT seed that can be reused (SubT, medium, reused) is higher than the demand for SubT seed that cannot be reused. Around 50 percent of farmer's are willing to pay a price of Rs 800 for a DT, short duration variety that can be reused but only 28 percent of farmers are willing to pay a similar price for a SubT, medium duration variety that can be reused. Similarly, around 45 percent of farmers are willing to pay a price of Rs 500 for a DT, short duration seed that cannot be reused whereas only 12 percent of farmers are willing to pay a similar price for SubT, medium duration seed that cannot be reused. In addition to this, we find a high demand for a super seed that incorporates both drought tolerant and submergence tolerant attributes. Around 42 percent of farmers are willing to pay a price of Rs 500 for a DT SubT seed that cannot be reused in the subsequent seasons. Thus, these curves depict increasing demand for DT and SubT technologies by farmers in Odisha.

8. Conclusion

Abiotic stresses such as droughts and floods lead to significant income and consumption losses for the rice-growing farmers in India. Rice seed varieties that have better tolerance to moisture stress conditions and submergence have potential to protect farmers' livelihoods. The objective of this study was to estimate farmers' valuations for various attributes in rice seeds. For the purpose, a discrete choice experiment methodology was used for 400 rice growing farmers in three districts of Odisha. The districts were carefully chosen so as to cover regions prone to droughts as well as regions prone to floods. The estimations have been done for the pooled sample as well as drought-prone and flood-prone regions separately. We find considerable heterogeneity in the farmers' valuations for various attributes in rice seeds, thus, we report results from a random parameter logit model. In the reported results, we account for attribute non-attendance.

We find that on average farmers in the pooled sample are willing to pay as high as Rs 448 for FSD and Rs 435 and Rs 430 for SSD and TSD attribute respectively, suggesting that farmers in Odisha prefer higher expected yields over and above lower yield variability. The other attributes highly valued by farmers are short duration, and being able to store grains and use it as seed in the subsequent seasons. By growing short duration varieties, farmers could escape droughts, floods etc. Moreover, short duration could allow farmers to grow other crops which could enhance their farm incomes. The WTP of farmers for submergence tolerance 10-15 days attribute is insignificant whereas WTP for 5-10 days is significant in the pooled sample. We also find that farmer's valuation for DT technology is significantly higher than their valuation for SubT technology.

Qualitatively the results are similar for the subsamples of drought-prone and the flood-prone regions, however, the WTP for all the attributes (except for submergence tolerance for 5-10 days, and grain can be stored and reused) is considerably higher in the submergence prone region as compared to the drought-prone region. This could probably be due to the socio-economic differences in our samples from the two regions. As is evident from the summary statistics, in our sample the farmers from the submergence prone region have a higher mean income, are more educated on average, and a higher proportion belongs to the general caste. We also find that while the marginal valuation for submergence tolerance for 10-15 days is positive and statistically significant for the farmers in the flood-prone region, it is insignificant for the farmers in the drought-prone region.

Apart from assessing the preferences of farmers, this study also analyzed heterogeneity in the preferences of farmers for various attributes. Our estimation results depict considerable heterogeneity in the preferences of farmers for attributes like short duration, medium duration, seed reusability and yield variability. In order to identify the possible sources of observed heterogeneity, interactions of household specific social and economic characteristics such as income and caste with various rice seed attributes were estimated. It finds that different group of farmers have a different valuation for various rice seeds attributes. While the higher income groups have a higher valuation for yield enhancing, submergence tolerance and short duration attributes, SSD, TSD and seed reusability attributes are valued more by lower income groups. Contrary to this, the non-scheduled caste groups have a higher valuation for almost all rice seed attributes as compared to the scheduled caste groups. The results are interesting and suggest that new and improved agricultural crop technologies such as submergence tolerance and drought tolerant rice seeds are highly valued by farmers in Odisha. But these technologies are valued differently by different socio-economic groups. In particular, the poor, who are resource constrained, have a lower valuation for submergence tolerance technologies whereas lower caste groups (SC&ST) have a lower valuation for both DT and SubT technologies. This in turn informs the government regarding the use of some appropriate measures (such as targeting of subsidies or compensation) so that these new and improved technologies are adopted equitably by the various groups and helps in ensuring food security in India.

In addition to this, we also estimate the individual level coefficients from the RPL model using some post estimation conditioning approaches. We further use these parameters to gain insight about the attributes ignored/irrelevant for farmers in a choice set. For this purpose, we followed the approach of Hess and Hensher (2010) and compute the coefficient of variation (COV) i.e. the ratio of the standard deviation and mean of the conditional distribution for each attribute level across 400 households. A COV greater than a certain threshold level implies a noisy distribution and could mean that this individual is ignoring that particular attribute in his decision making among various rice seed alternatives. We worked with various threshold values of 2, 2.5 and 3. It finally constraints the coefficient of marginal utility of various attributes for those households that exceed the threshold level and estimates the constrained RPL model.

The results suggest that farmers have a high WTP for higher expected yields as compared to lower yield variability. The submergence tolerance 10-15 days and medium duration attribute are still insignificant in the constrained RPL model but the valuation for submergence tolerance 5-10 days, short duration and seed reusability has increased as compared to the unconstrained model. There is lesser degree of heterogeneity in farmer's preferences for various attributes as evidenced from a lower standard deviation estimates for almost all attributes as compared to the unconstrained model.

The individual level coefficients were also utilized to estimate the demand curves for various hypothetical bundle of rice seeds such as DT short duration seed can't be reused Vs DT short duration seed can be reused attributes, ST short duration seed can be reused Vs ST short duration seed can't be reused attribute. In addition to this, the demand curve is derived for a hypothetical super seed comprising both the DT and ST attributes. We find a high WTP for all such combination of seed attributes. Thus, information regarding the potential demand for such new and improved varieties of rice seeds would encourage the public and private sector for the further development and dissemination of such technologies and could also promote successful public- private partnerships among them.

The results from our study would be useful for researchers developing these new technologies in determining the traits they should focus on. They would also be useful in guiding public and private sector investment in the development and delivery of such technologies.

Our estimation results also depict considerable heterogeneity in the preferences of farmers for attributes like short duration, medium duration, seed reusability and yield variability. Future research can explore the role of socio-economic and behavioral factors causing this heterogeneity and policy interventions that ensure that new technologies are accessible to all sections of the society.

Appendix A.1

Table 1. Choice set attributes and respective levels

Attribute	Levels
Drought tolerance	"FSD": Yields 55qtl/ha, 32qtl/ha, 16qtl/ha‡
	"SSD": Yields 53qtl/ha, 32qtl/ha, 16qtl/ha‡
	"TSD": Yields 53qtl/ha, 22qtl/ha, 16qtl/ha‡
Submergence tolerance	0-5 days, 5-10 days, 10-15 days
Duration	Short (90-120 days), Medium (120-135 days), Long (135-165) days.
Seed type	0: Seeds must be purchased every year 1: Grains which can be stored and used as seed in the next season
Price	Rs 15, Rs 25, Rs 50, Rs 150, Rs 220, Rs 300.

‡ These figures correspond to yields under normal conditions, moderate drought stress conditions, and extreme drought stress conditions, respectively. A quintal is a unit of mass commonly used in Odisha, equivalent to 100 kg.

Table 2: Summary statistics of households in the sample

Household Characteristics	Pooled	Drought prone	Submergence prone
Sample Size	400	200	200
Average size of household	5.24[2.012]	4.9[1.701]	5.6 [2.227]
Mean age of household head	52.88[13.68]	50.46[13.33]	55.30[13.60]
Gender of household head			
Male	387(96.75)	189(94.5)	198(99)
Female	13(3.25)	11(5.50)	2(1)
Education of household head			
Illiterate	69(17.25)	47(23.5)	22(11)
1-5 class	154(38.5)	82(41)	72(36)
6-12 class	161(42.25)	63(31.5)	98(49)

Bachelor degree or higher	16(4)	8(4)	8(4)
Religion			
Hindu	383(95.75)	183(91.5)	200(100)
Muslim	17(4.25)	17(8.50)	0(0)
Caste			
General	97(24.25)	34(17)	63(31.5)
OBC	161(41.25)	93(46.5)	68(34)
SC	100(25)	33(16.5)	67(33.5)
ST	31(7.75)	30(15)	1(0.5)
Other	11(2.75)	10(5)	1(0.5)
Mean total annual income Of the household	87823.74 [92183.86]	76569.96 [95995.04]	99077.52 [86998.93]

Table 3: Estimation of Random-parameter logit Results: Total Attribute attendance

Variables (Choice: Dependent)	Pooled	Drought -prone	Submergence-prone
Random Utility Parameters			
FSD-Yields 55qtl/ha,32qtl/ha,16qtl/ha	**1.358(0.101)*****	**1.384(0.142)*****	**1.469(0.152)*****
SSD-Yields 53qtl/ha,32qtl/ha,16qtl/ha	**1.429(0.097)*****	**1.447(0.127)*****	**1.349(0.153)*****
TSD-Yields 53qtl/ha,22qtl/ha,16qtl/ha	**1.298(0.107)*****	**1.211(0.145)*****	**1.366(0.173)*****
Short duration	**0.793(0.175)*****	**0.692(0.187)*****	**1.144(0.290)*****
Medium duration	**0.136(0.118)**	**0.112(0.127)**	**-0.051(0.221)**
Sub-T(5-10 days)	**0.263(0.072)*****	**0.311(0.094)*****	**0.236(0.117)****
Sub-T(10-15 days)	**0.043(0.088)**	**-0.013(0.114)**	**0.274(0.135)****
Grain cannot be saved	**-0.786(0.103)*****	**-1.145(0.163)*****	**-0.474(0.134)*****
Non-random parameter			
Price	**-.0034(0.0003)*****	**-.0038(0.004)*****	**-0.0031(0.0004)*****
Distribution of random parameters			
Sd. FSD	***1.021(0.110)******	**1.028(0.137)*****	**0.862(0.173)*****
Sd.SSD	***0.857(0.113)******	**-0.712(0.153)****	**-0.990(0.224)*****
Sd.TSD	***1.041(0.110)******	**0.953(0.149)*****	**1.277(0.193)*****
Sd.Short duration	***2.814(0.187)******	**2.314(0.199)*****	**3.802(0.389)*****
Sd.Medium duration	***1.715(0.160)******	**1.163(0.159)*****	**2.201(0.243)*****
Sd. Sub-T(5-10days)	***0.595(0.109)******	**0.458(0.182)*****	**0.874(0.183)*****
Sd.Sub-T(10-15 days)	***1.053(0.110)******	**0.845(0.186)*****	**1.099(0.150)*****
Sd.Grain cannot be saved	***1.620(0.114)******	**0.815(0.178)*****	**-0.847(0.156)*****

Likelihood ratio	**1648.39*** **	**655.15*** **	**1012.57*** **
Log-likelihood	**-3858.69**	**-1978.31**	**-1849.33**
Rho	**0.171**	**0.138**	**0.209**
AIC	**7736.38**	**3974.6**	**3716.6**
BIC	**7791.05**	**4024.0**	**3766.0**
Number of observations	**3600**	**1800**	**1800**

Figures in brackets denote standard errors, Sd stands for standard deviation and *,**,* denote significance at 1 percent, 5percent and 10 percent respectively.*

Table 3.1: WTP Estimates (RPL model) for the pooled sample with confidence intervals.

Variables	Mean WTP Estimates In Rs/Kg	Confidence Interval	
		Lower	Upper
FSD	395.5	322.5	469.4
SSD	417	340.3	493.2
TSD	378.5	306.5	450.4
Short duration	231	123.8	338.9
Grain cannot be saved	-229	-300.6	-158.0
SubT (5-10 days)	84.5	42.4	126.8
SubT(10-15 days)	25.5	-18.8	69.6

Table 3.2: WTP estimates for drought prone region

Variables	Mean WTP Estimates in Rs/Kg	Confidence Interval	
		Lower	Upper
FSD	357	271.1	443.7
SSD	373	288.2	458.8
TSD	312	231.9	393.3
Short duration	179	79.1	278.5
Grain cannot be saved	-295	-398.0	-193.3
Sub-T (5-10 days)	80	29.1	131.5
Sub-T(10-15 days)	-3.45	-61.2	54.3

Table 3.3: WTP estimates for submergence prone region

Variables	Mean WTP Estimates in Rs/Kg	Confidence Interval	
		Lower	Upper
FSD	461	331.6	590.4
SSD	423	300.3	546.6
TSD	428	305.0	552.3
Short duration	359	162.1	556.1

Grain cannot be saved	**-148**	**-240.0**	**-57.6**
SubT (5-10 days)	**74**	**-2.14**	**150.3**
SubT (10-15 days)	**86**	**-0.05**	**172.3**

Table 4: RPL Interaction with Income and WTP estimates

Variables	**Pooled**		**WTP**	
(Choice: Dependent)		**Lower**		**Upper**
Random Utility Parameters				
FSD. High Inc	**1.69(0.141)*****	**318.3**	**400**	**480.8**
SSD. High Inc	**1.60(0.129)*****	**302**	**380**	**457**
TSD. High Inc	**1.41(0.145)*****	**259.8**	**334**	**407.5**
Short duration. High Inc	**1.49(0.224)*****	**230.2**	**353**	**476.1**
Medium duration. High Inc	**0.459(0.129)*****	**46.7**	**108.5**	**178.3**
SubT (5-10 days). High Inc	**0.561(0.092)*****	**81.8**	**132**	**183.1**
SubT (10-15 days). High Inc	**0.374(0.114)*****	**33.3**	**88**	**143.3**
Grain cannot be saved. High Inc	**-0.976(0.123)*****	**-301.4**	**-230.5**	**159.7**
FSD. Low Inc	**0.838(0.101)*****	**266**	**392**	**518.4**
SSD. Low Inc	**0.895(0.094)*****	**284.4**	**419**	**553.3**
TSD. Low Inc	**0.750(0.104)*****	**235.1**	**351**	**466.9**
Short duration. Low Inc	**0.278(0.117)****	**16.9**	**130**	**243.4**
Medium duration. Low Inc	**0.134(0.080)***	**-12.9**	**63**	**138.5**
SubT(5-10 days).Low Inc	**0.089(0.076)**	**-29.8**	**42**	**113.2**
SubT(10-15 days).Low Inc	**-0.037(0.076)**	**-88.4**	**-18**	**53.06**
Grain cannot be saved. Low Inc	**-0.515(0.081)*****	**-349.3**	**-241**	**132.6**
Non-random parameter				
Price. High Inc	**-0.0042(0.0004)*****			
Price. Low Inc	**-0.0021(0.0003)*****			
Distribution of random parameters				
Sd. FSD. High Inc	**0.954(0.199)*****	**Sd. FSD. Low Inc**		**0.534(0.130)*****
Sd. SSD. High Inc	**0.714(0.147)*****	**Sd. SSD. Low Inc**		**0.435(0.110)*****
Sd.TSD. High Inc	**1.07(0.073)*****	**Sd.TSD. Low Inc**		**-0.535(0.103)*****
Sd. Short Dur. High Inc	**3.21(0.248)*****	**Sd. Short Dur. Low Inc**		**1.61(0.141)*****
Sd. Medium Dur. High Inc	**1.53(0.163)*****	**Sd. Medium Dur. Low Inc**		**0.547(0.102)*****
Sd. SubT(5-10). High Inc	**0.092(0.224)**	**Sd. SubT(5-10). Low Inc**		**0.520(0.106)*****
Sd.SubT(10-15). High Inc	**0.841(0.132)**	**Sd. SubT(10-15). Low Inc**		**-0.189(0.128)**
Sd.Grain cannot saved. High Inc	**1.51(0.155)*****	**Sd. Grain cannot saved. Low In**		**0.879(0.099)*****
Log Likelihood	**-3978.16**			**3600**
Rho	**0.14**	**Number of Observations LR test**		**1325.19*****

Figures in brackets denote standard errors, Sd stands for standard deviation and *,**,* denote significance at 1 percent, 5percent and 10 percent respectively.*

Table 5: RPL Interaction with Caste and WTP estimates

Variables (Choice: Dependent)	Pooled	Lower	WTP	Upper
Random Utility Parameters				
FSD. Non-SCST	**1.29(0.104)*****	**377.9**	**499**	**620.2**
SSD. Non SCST	**1.40(0.096)*****	**412**	**544**	**675.5**
TSD. Non SCST	**1.09(0.110)*****	**314.9**	**423**	**531.5**
Short duration. Non SCST	**0.913(0.144)*****	**215.8**	**353**	**489.6**
Medium duration. Non SCST	**0.139(0.191)**	**-15.9**		**123.9**
SubT(5-10 days). Non SCST	**0.329(0.076)*****	**61.3**	**127**	**193.4**
SubT(10-15 days). Non SCST	**0.114(0.090)**	**-24.6**		**113.3**
Grain cannot be saved. Non SCST	**-0.76(0.098)*****	**-401.4**	**-296.3**	**191.0**
FSD. SCST	**0.765(0.141)*****	**130.3**	**205**	**280.4**
SSD. SCST	**0.689(0.133)*****	**113.1**	**185**	**256.9**
TSD. SCST	**0.971(0.143)*****	**183.7**	**260**	**337.6**
Short duration. SCST	**1.13(0.277)*****	**148.2**	**306**	**463.6**
Medium duration. SCST	**0.418(0.116)*****	**46.0**	**112.0**	**178.5**
SubT(5-10 days). SCST	**0.159(0.105)***	**-13.9**	**43**	**99.5**
SubT(10-15 days). SCST	**0.016(0.110)-**	**-53.7**		**62.8**
Grain cannot be saved. SCST	**0.590(0.120)*****	**-234.8**	**-158.5**	**-82.2**
Non-random parameter				
Price. Non SCST	**-0.0025(0.0003)*****			
Price. SCST	**-0.0037(0.0004)*****			
Log Likelihood	**-3951.5**			
Rho	**0.15**			
LR test	**1414.83*****			
Number of Observations	**3600**			

Figures in brackets denote standard errors, Sd stands for standard deviation and *,**,* denote significance at 1 percent, 5percent and 10 percent respectively.*
**SCST comprises Scheduled caste and Scheduled Tribe households whereas Non-SCST includes households belonging to general, OBC and other caste.*

Table 6: Summary Statistics of Attribute Non-Attendance in terms of CV.

Attributes	No. of households with COV > 2.5
FSD	15

SSD	**4**
TSD	**22**
SubT(5-10days)	**93**
SubT (10-15days)	**74**
Short Duration	**34**
Medium Duration	**58**
Seed Reusability	**33**

Table 7 Results from Constrained RPL model (Halton draws = 400).

Variables (Choice: Dependent)	**Coefficient**	**Standard Error**
Random Utility Parameters		
FSD-Yields 55qtl/ha,32qtl/ha,16qtl/ha	**1.584*** **	**0.101**
SSD-Yields 53qtl/ha,32qtl/ha,16qtl/ha	**1.538*** **	**0.099**
TSD-Yields 53qtl/ha,22qtl/ha,16qtl/ha	**1.520*** **	**0.105**
Short duration	**0.994*** **	**0.159**
Medium duration	**0.135**	**0.132**
SubT(5-10 days)	**0.492*** **	**0.078**
SubT(10-15 days)	**0.010**	**0.087**
Grain cannot be saved	**-0.883*** **	**0.105**
Non-random parameter		
Price	**-0.0035*** **	**0.0003**
Distribution of random parameters		
Sd. FSD	***0.897**** **	**0.114**
Sd.SSD	***0.918**** **	**0.110**
Sd.TSD	***-0.888**** **	**0.115**
Sd.Short duration	***2.831**** **	**0.179**
Sd.Medium duration	***1.710**** **	**0.144**
Sd. SubT(5-10days)	***0.410**** **	**0.125**
Sd.SubT(10-15 days)	***-0.780**** **	**0.100**
Sd.Grain cannot be saved	***1.598**** **	**0.118**
Log-likelihood		**-3747.60**
Rho (Pseudo R2)		**0.289**
AIC		**7511.2**
BIC		**7560.2**
Number of observations		**3600**

****,**,* denotes significance at one percent, five percent and ten percent respectively.*

Table 7.1: WTP Estimates derived from constrained RPL model for the pooled sample

Variables	**Mean WTP Estimates in Rs/kg**	**Confidence Interval**	
		Lower	**Upper**
FSD	**448**	**373.3**	**525.7**

SSD	**435**	**358.5**	**511.2**
TSD	**430**	**356.6**	**503.2**
Short duration	**281**	**182.6**	**379.7**
Grain cannot be saved	**-250**	**-322.1**	**-177.3**
SubT (5-10 days)	**139**	**89.3**	**189.1**

Table 8: Results from constrained RPL model for the subsamples

Variables (Choice: Dependent)	Drought -prone	Submergence-prone
Random Utility Parameters		
FSD	**1.426(0.114)*****	**1.233(0.127)*****
SSD	**1.393(0.112)*****	**1.250(0.121)*****
TSD	**1.286(0.125)*****	**1.265(0.135)*****
Short duration	**0.526(0.142)*****	**0.598(0.217)*****
Medium duration	**0.166(0.095)***	**0.234(0.159)**
SubT(5-10 days)	**0.534(0.088)*****	**0.453(0.100)*****
SubT(10-15 days)	**-0.017(0.091)**	**0.184(0.108)***
Grain cannot be saved	**-1.006(0.018)*****	**-0.469(0.095)*****
Non-random parameter		
Price	**-0.0035(0.0003)*****	**-0.0025(0.0003)*****
Distribution of random parameters		
Sd. FSD	**0.620(0.131)*****	**0.874(0.140)*****
Sd.SSD	**0.768(0.144)**	**0.766(0.163)*****
Sd.TSD	**0.726(0.130)*****	**1.078(0.155)*****
Sd.Short duration	**1.976(0.178)*****	**2.617(0.239)*****
Sd.Medium duration	**0.480(0.114)*****	**-1.820(0.159)*****
Sd. SubT(5-10days)	**0.265(0.119)*****	**-0.269(0.178)***
Sd.SubT(10-15 days)	**-0.176(0.192)****	**0.582(0.137)*****
Sd.Grain cannot be saved	**1.353(0.126)*****	**0.670(0.132)*****
Log-likelihood	**-1946.28**	**-1891.99**
Rho	**0.239**	**0.292**
AIC	**3908.56**	**3801.98**
BIC	**3958.06**	**3849.5**
Number of observations	**1800**	**1800**

***,**,* denotes significance at one percent, five percent and ten percent respectively.

Table 8.1 WTP estimates for drought prone region

Variables	Mean WTP Estimates	Confidence Interval	
		Lower	Upper

FSD	398	310.8	485.2
SSD	388	302.2	475.2
TSD	359	277.3	440.6
Short duration	147	65.0	228.5
Medium duration	46.5	-6.36	99.4
Grain cannot be saved	-280.8	-366.7	-194.8
SubT(5-10 days)	149	92.1	306.0

Table 8.2: WTP estimates for submergence prone region

Variables	Mean WTP Estimates	Confidence Interval	
		Lower	Upper
FSD	490	342.2	637.3
SSD	496	346.4	646.2
TSD	502	350.6	653.9
Short duration	238	47.2	428.0
Medium duration	93	-34.6	220.6
Grain cannot be saved	-186	-280.3	-92.4
SubT (5-10 days)	180	81.1	279.2
SubT (10-15 days)	73	-13.6	159.8

Figure 1. Sample Choice Experiment Design

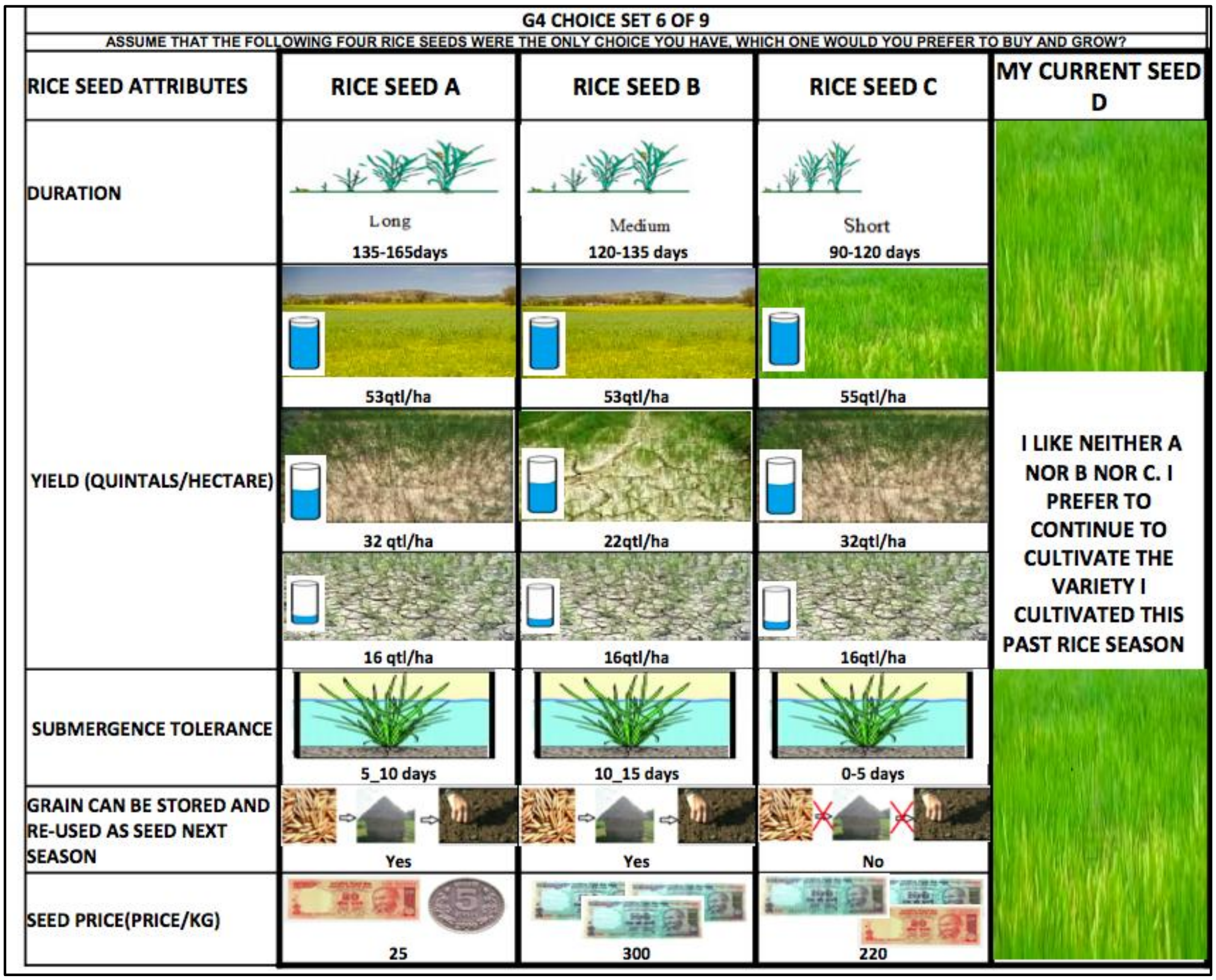
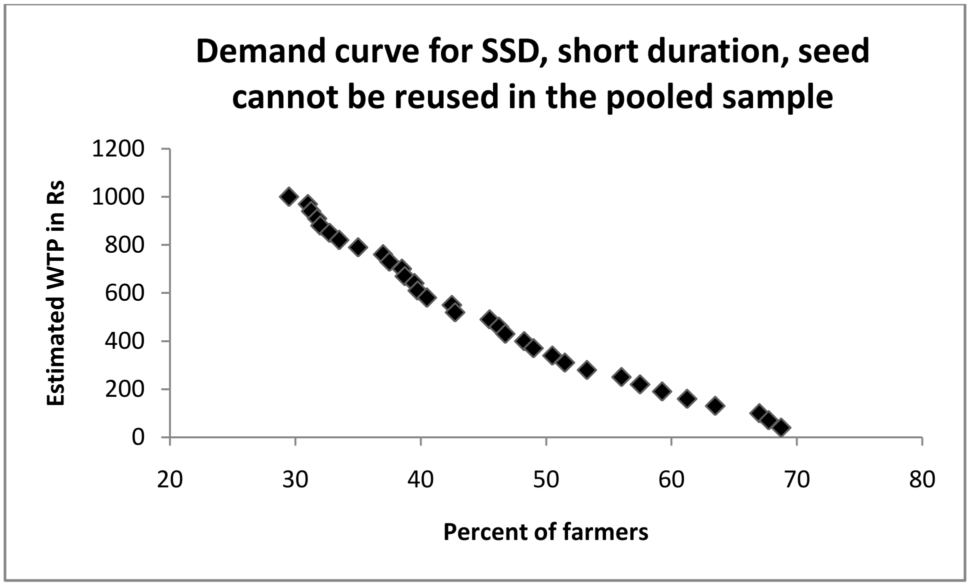
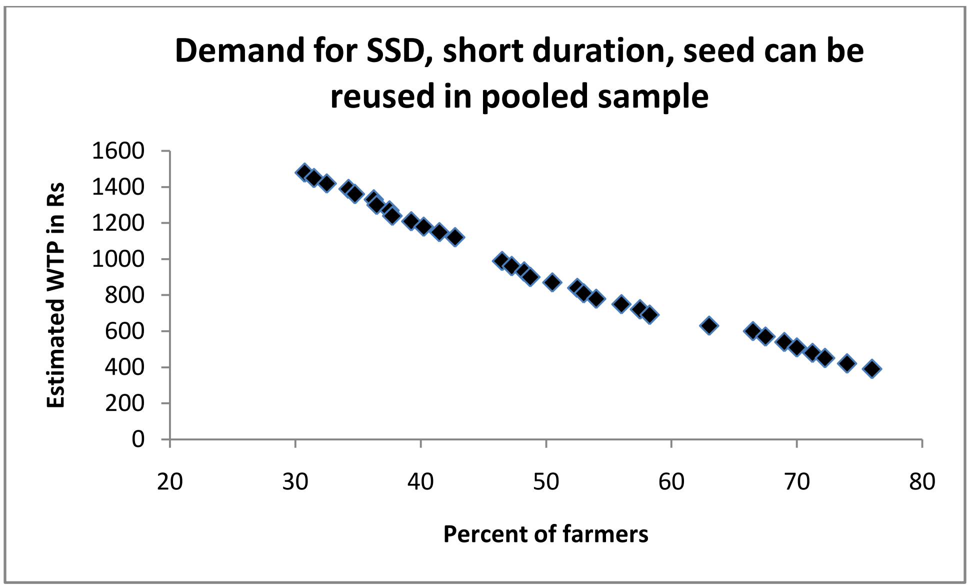
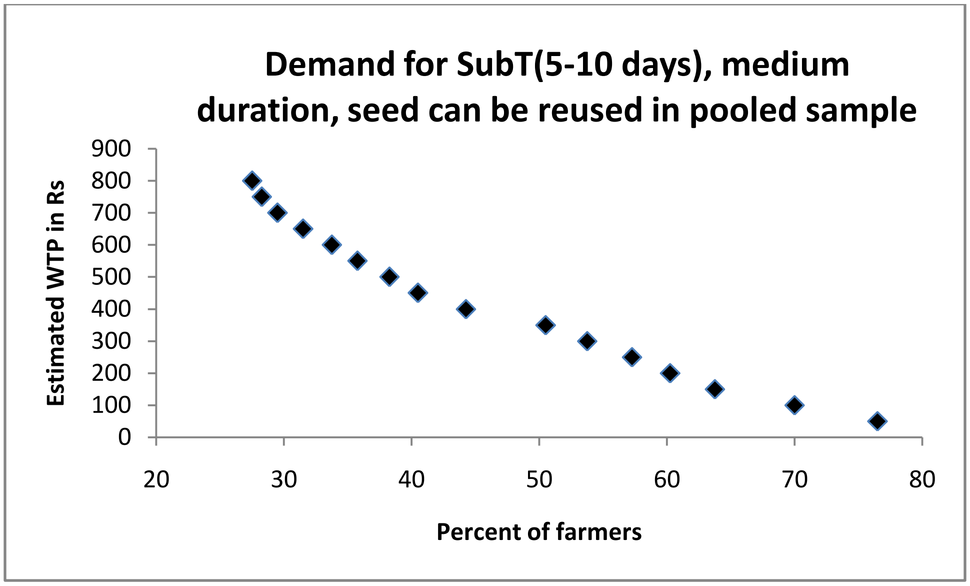


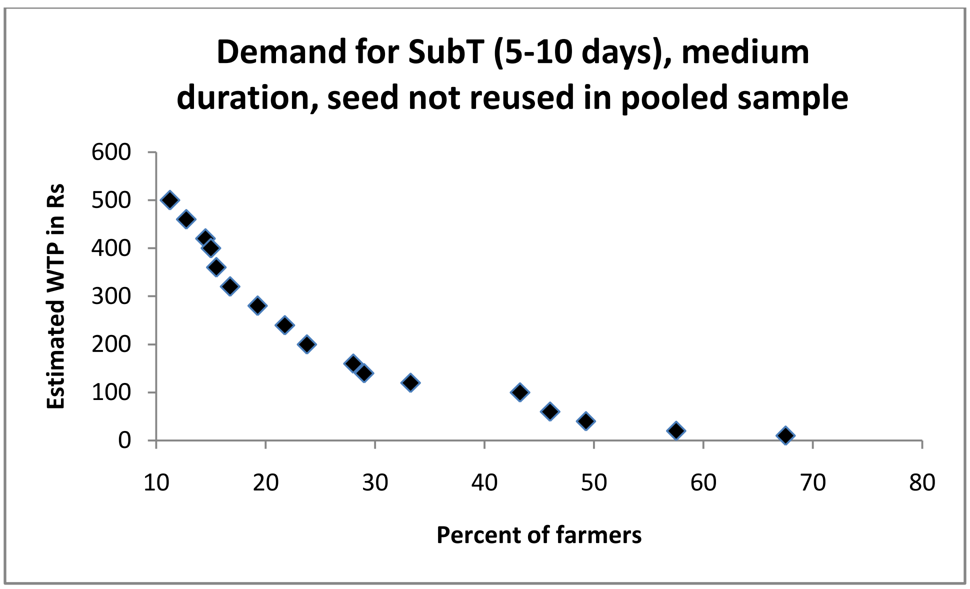
Fig 2 Location map of India

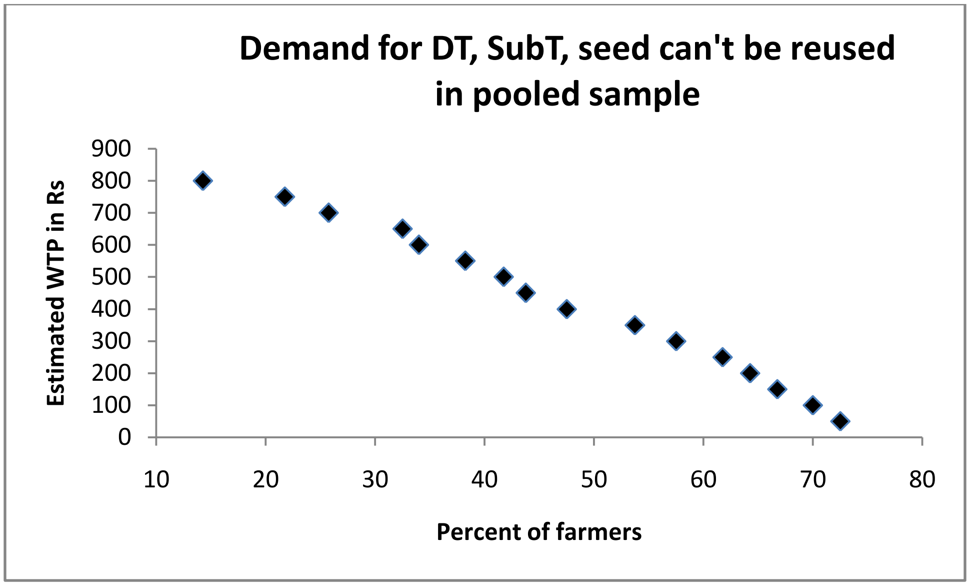
Figure 3: Derived demand curves from individual WTP estimates


Demand curve for SSD, short duration, seed cannot be reused in the pooled sample
Estimated WTP in Rs
1200
1000
800
600
400
200
0
20
30
40
50
60
70
80
Percent of farmers


Demand for SSD, short duration, seed can be reused in pooled sample
Estimated WTP in Rs
1600
1400
1200
1000
800
600
400
200
0
20
30
40
50
60
70
80
Percent of farmers


Demand for SubT(5-10 days), medium duration, seed can be reused in pooled sample
Estimated WTP in Rs
900
800
700
600
500
400
300
200
100
0
20
30
40
50
60
70
80
Percent of farmers


Demand for SubT (5-10 days), medium duration, seed not reused in pooled sample
Estimated WTP in Rs
600
500
400
300
200
100
0
10
20
30
40
50
60
70
80
Percent of farmers



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