**Farmers' Heterogeneous Valuation of Laser Land Leveling in Eastern Uttar Pradesh: An**

**Experimental Auction Approach to Informing Segmentation & Subsidy Strategies**

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### Abstract

Demand heterogeneity often makes it profitable for firms to price and promote goods and services differently in different market segments. When private consumption brings public benefits, this same heterogeneity can be used to develop targeted public subsidies. We explore the design of public-private targeting and segmentation strategies in the case of a resource-conserving agricultural technology in India. To understand farmers' heterogeneous demand for Laser Land Leveling (LLL), we conducted an experimental auction for LLL services with an integrated randomized control trial to estimate the private benefits of the technology. We use graphical and econometric approaches to characterize farmer demand for LLL. We then add detailed cost data from LLL providers to simulate and evaluate several potential targeted delivery strategies based on measures of cost effectiveness of expanded diffusion of LLL and market surplus in a welfare framework. These simulations demonstrate inherent tradeoffs between increasing the amount of land that is leveled and expanding the number of farmers adopting the technology. While segmenting and targeting are popular elements of many public-private partnerships to develop and disseminate agricultural technologies, formulating and implementing effective delivery strategies requires a rich understanding of costs, benefits and demand. Our experimental approach generates such an understanding and may be relevant in other contexts.

## 1. INTRODUCTION

For most of the rural poor in developing countries, improving day-to-day quality of life requires improvements in agricultural productivity. With the gradual reduction of government support for public agricultural research, extension, and marketing in many of these settings, the dissemination of new agricultural techniques and technologies is increasingly shaped by the private sector (Feder, et al. 2001). When the private agro-services sector thrives, farmers often benefit from better information, more options and, ultimately, higher productivity. For many agricultural technologies, however, the private sector lacks the incentives and information needed to successfully serve the needs of poor farmers. In these cases, a variety of mechanisms are often proposed to encourage broader technology dissemination, ranging from targeted subsidies provided by the public sector to marketing strategies such as promotional discounts used by the private sector (Aker, et al. 2005).

However, the lack of information about poor farmers' valuation of new agricultural technologies typically remains a constraint for both public and private sector providers. Consequently, even when there is a political or corporate willingness to target poor farmers with support, a vague and incomplete understanding of how famers value a technology differently often prevents famers value a technology differently often prevents this willingness and these targeted support mechanisms from translating into agricultural productivity gains for the poor.

We aim to fill this void in the case of a new agricultural technology in Eastern Uttar Pradesh, India (EUP). We use experimental auctions to better understand heterogeneity of farmers' demand for Laser Land Leveling (LLL) services in this region. Technology demand can be shaped by a variety of farm and farmer characteristics such as farm size, market access, risk preferences, education, experience, wealth, access to information, and access to credit. Understanding how demand varies across observable variables is a necessary first step at designing market segmentation strategies. We use standard econometric analysis in this first step as a point of departure for devising an approach to more rigorously and more directly test segmentation and targeting strategies. Specifically, we construct farmer-level demand curves based on our experimental auction data. We use bootstrapping techniques to aggregate these curves into probabilistic demand curves for our sample farmers and for specific sub-sets of farmers. Based on detailed cost data from our LLL provider, we characterize the supply side as well. These probabilistic demand curves together with our LLL costs enable us to test specific targeting strategies based on several metrics, including LLL expansion over acres and households. Using a welfare framework, we also estimate the market surplus effects of these strategies and the deadweight loss associated with strategies that involve targeted subsidies.

Farmers in the rice-wheat farming systems of the Indo-Gangetic Plain typically flood irrigate their fields using water extracted from tube wells using diesel pumps. Farmers tend to flood each plot to its highest point to ensure that the entire field is fully irrigated. Whereas farmers do not pay for water directly, they do pay for diesel and therefore benefit from water conservation. With a more uniformly leveled field, it is possible to dramatically reduce water usage (Jat, et al. 2006). While any public benefits associated with reduced groundwater pumping and reduced diesel fuel consumption in a given region are shared, the private benefits of LLL can vary widely across different farmers and plots. This mix of public benefits and heterogeneous private benefits associated with LLL makes novel market segmentation strategies and targeted subsidies particularly potent as a means of improving social welfare.

Experimental auctions have become a popular approach to better understand heterogeneity in individual valuation of goods and services. As argued by Lusk and Shogren (2008, p.4), "relative to other value elicitation techniques, experimental auctions provide the richest description of heterogeneity in valuations across people and goods with minimal assumptions." Because such auctions are binding, hypothetical bias is mitigated (Harrison and Rutström 2008). Experimental auctions have been used widely to assess consumer valuation of agricultural products in developed countries. Indeed, food is by far the most commonly auctioned item, where valuation dimensions include quality attributes (e.g., marbling in pork chops), production conditions (e.g., organic, genetically modified organisms, growth hormones), and risk and information (e.g., food safety) (Alfnes and Rickertsen 2003; Hayes, et al. 1995; Melton, et al. 1996). In developing countries, experimental auctions have shed light on heterogeneity of valuation of health and nutrition products such as bed nets, fortified foods, and infant foods of certified quality (De Groote, et al. 2010; Dupas 2010; Hoffmann, et al. 2009; Masters and Sanogo 2002). Our experimental auction approach to understanding farmers' valuation of LLL builds on these recent efforts and incorporates a WTP-conditioned lottery to enable the rigorous evaluation of LLL impacts.

## 2. LASER LAND LEVELING IN INDIA

LLL is a resource conserving technology new to EUP, but available in other areas of the Indo-Gangetic Plains (IGP). In surface irrigated rice-wheat systems in the IGP, 10-25% of irrigation water is lost because of poor management and uneven fields. Uneven fields also lead to inefficient use of fertilizers and chemicals, increased biotic and abiotic stress, and lower yields (Jat, et al. 2006). Laser leveling is a process of smoothing the land surface using a laser-equipped drag scraper for precision resulting in plots that are leveled to ±2 cm. In comparison, traditional leveling methods used in the region have a precision of ±4-5 cm.

After LLL was introduced in western Uttar Pradesh in 2001, the number of laser land levelers rose to 925 and land leveled grew to 200,000 hectares by 2008. LLL trials in rice-wheat systems of the IGP have found 10-30% irrigation savings, 3-6% effective increases in farming area, 6-7% increases in nitrogen use efficiency, 3-19% increases in yield, and increases in annual farm revenue of $200-300 per hectare (Jat, et al. 2006). LLL could also have public benefits in the form of reduced groundwater depletion, chemical use, and greenhouse gas emissions. Jat et al. (2006) estimate that extended use of LLL to 2 million hectares of rice-wheat land in the IGP could save 1.5 million hectare-meters of irrigation water and 200 million liters of diesel, improve crop yields by $500 million, and reduce greenhouse gas emissions by 0.5 million metric tons over three years. These crude extrapolations assume that LLL benefits elsewhere in the IGP region are similar to those observed in the more developed northwestern portions of the IGP. Given the substantial differences between the eastern and western IGP, these extrapolations may be misleading. While our scope in this paper is to explore delivery strategies in EUP, a companion paper estimates the private and potential public benefits of LLL in this heterogeneous region.

In the western regions of the IGP, most farmers access LLL via custom hire service. Since a precisely leveled plot may not need re-leveling for several years (depending on the soil type and cultivation and harvesting practices), hiring out these LLL services may be optimal even for farmers with relatively large plots. The dominant pricing model for these services is a flat price per hour of leveling. To date, LLL providers have relied almost exclusively on word-of-mouth advertising. To expand into a new area, they often will contact a farmer and offer to level a plot with a money-back guarantee: if the farmer is not satisfied after the service is provided, he need not pay.

## 3. A THEORETICAL FRAMEWORK

Many technology adoption models use a dichotomous variable for adoption/non-adoption that is the observable manifestation of the expected net benefits of adoption (Feder, Just and Zilberman, 1985). Other models examine intensity of adoption to account for either risk management, experimentation, or a combination thereof (Feder 1980; Leathers and Smale 1991; Smale, et al. 1994). Hazard models can be used to estimate time until adoption of a new technology (Abdulai and Huffman 2005). In our case, we have a continuous measure of farmers' valuation of a new technology based on WTP elicited in our experimental auction for LLL services. This section provides a microeconomic foundation for WTP for a new technology in order to motivate econometric specifications to understand determinants of farmers' demand for LLL. It then describes the aggregation of these WTP measures as a means of characterizing market demand for LLL and assessing the welfare implications of different targeting strategies. We see

these different analytical perspectives on demand to be complementary in important ways and use the framework laid out in this section to structure our subsequent empirical analysis.

A producer's WTP for a technology is based on the difference in indirect utility (in monetary units) between a scenario with and without the technology, allowing the optimal amounts of other inputs to differ in these two scenarios. For simplicity, we assume farmers are risk-neutral, profit-maximizers with the option of leveling plots using LLL custom hire services—an unfamiliar technique to more precisely remedy a very familiar problem.[1] We assume the leveling technologies are scale-neutral and incur no fixed costs to the farmer.[2] Farmer $i$ maximizes expected profits for each plot $j$ and for each technology $k$, where $N$=no leveling and $L$=LLL:

$$\max_{\mathbf{x}_{ij}^k} E\pi_{ij}^k = E\left[ y_{ij}^k\left( \mathbf{z_i}, \boldsymbol{\varphi}_{\mathbf{j}}^{k\prime}\mathbf{x}_{\mathbf{ij}}^k, \mathbf{s_j} \right) - \boldsymbol{\omega}_{\mathbf{i}}'\mathbf{x}_{\mathbf{ij}}^k \right] \text{ for } k \in \{N, L\} \tag{1}$$

where $y_{ij}^k$ is the expected value of total annual production, $\mathbf{z_i}$ is a vector of farmer characteristics, $\mathbf{x}_{\mathbf{ij}}^k$ is a vector of $h=1,2,\ldots,H$ inputs (e.g., water, labor, fertilizer, chemicals), $\mathbf{s_j}$ is a vector of plot characteristics, and $\boldsymbol{\omega}_{\mathbf{i}}$ is a vector of farmer-specific prices.[3] The vector $\boldsymbol{\varphi}_{\mathbf{j}}^k$ contains an efficiency parameter for each input $h$ that indicates the proportion of the input that goes to crop production, which are a function of plot characteristics, $\varphi_{jh}^k = \varphi_{jh}^k(\mathbf{s_j})$. For a given vector $\mathbf{s_j}$ and flood irrigated water ($h=1$), we assume $0 < \varphi_{j1}^N < \varphi_{j1}^L \leq 1$ since a portion of the water applied to an unleveled plot is used only to raise the water level to the highest point rather than to increase crop production directly. For other inputs ($h=2,\ldots H$), we assume $0 < \varphi_{j1}^N \leq \varphi_{j1}^L \leq 1$ and expect this relationship will hold with strict inequality for some inputs based on (i) the pervasive complementarities between water use efficiency and the efficiency of inputs

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[1] In the context of the experimental auction, the decision is made in two stages. At the time of the auction, the farmer can either adopt LLL or not. If she adopts LLL, the technology choice is made. If not, she can wait several weeks to decide whether to use traditional leveling or to not level (but LLL is no longer an option). For modeling purposes, we assume the farmer is only choosing between LLL and no leveling since relatively few of our farmers (11%) have recently leveled their land using traditional leveling services.

[2] This is not entirely implausible given that the overwhelming majority of leveling is done by custom hire on small farmers in Northern India. In our sample, 3% of farmers have their own traditional leveler.

[3] Prices can be either market or shadow prices. While prices for all inputs might vary depending on transaction costs, differential irrigation costs present the main motivation for allowing the model to accommodate farmer-specific input prices. Most farmers rely primarily on diesel-powered pumps (86%), for which they pay fuel costs. Some farmers, however, use canal irrigation for which they do not pay for out of pocket, but may face quantity constraints.

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such as fertilizer and chemicals and (ii) more uniform crop establishment, which makes input demands across a given plot less variable. We will ultimately test these complementarities empirically.

Once the farmer solves problem (1) for $\mathbf{x}_{\mathbf{ij}}^{k*}$ for all technology choices, the expected net benefits of LLL emerge from a simple comparison of expected profits with and without laser leveling:

$$\Delta E\pi_{ij}^{*} = E\left[ y_{ij}^{L}\left(\mathbf{z_i},\boldsymbol{\varphi}_{\mathbf{j}}^{L'}\mathbf{x}_{\mathbf{ij}}^{L*},\mathbf{s_j}\right) - \boldsymbol{\omega}_{\mathbf{i}}'\mathbf{x}_{\mathbf{ij}}^{L*}\right] - E\left[ y_{ij}^{N}\left(\mathbf{z_i},\boldsymbol{\varphi}_{\mathbf{j}}^{N'}\mathbf{x}_{\mathbf{ij}}^{N*},\mathbf{s_j}\right) - \boldsymbol{\omega}_{\mathbf{i}}'\mathbf{x}_{\mathbf{ij}}^{N*}\right] \qquad (2)$$

Farmer $i$'s maximum WTP for LLL services on plot $j$ hinges on this change in expected profits:

$$WTP_{ij} = \begin{cases} \Delta E\pi_{ij}^{*} & if\ 0 < \Delta E\pi_{ij}^{*} < c_i \\ c_i & if\ 0 < c_i < \Delta E\pi_{ij}^{*} \\ 0 & if\ \Delta E\pi_{ij}^{*} < 0 \end{cases} \qquad (3)$$

where $c_i = c_i(\mathbf{z_i})$ indicates the farmer's liquidity constraint, which is function of farmer assets, cash on hand, access to credit, and other characteristics in $\mathbf{z_i}$. If this liquidity constraint is binding, then a farmer's WTP will reflect a mix of this constraint and the expected net benefits associated with the technology.

Equations (2) and (3) suggest a reduced-form representation of farmers' WTP that can be estimated econometrically as:

$$WTP_{ij} = f\left(\mathbf{z_i},\mathbf{s_j},\boldsymbol{\omega}_{\mathbf{i}},c_i \middle| \boldsymbol{\beta}\right) + \varepsilon_{ij} \qquad (4)$$

This familiar 'determinants of demand' estimation is a mainstay of analysis of data collected in experimental auctions or contingent valuation exercises. Based on the dominant conditional-mean regression approach, the coefficients in the parameter vector $\boldsymbol{\beta}$ indicate how – on average – different farmer and plot characteristics influence a farmer's valuation of LLL for a given plot *ceteris paribus*. Both of these features of the dominant approach – that coefficients provide the average relationship between an independent and dependent variable all else equal – merit some discussion. First, as described by Lusk and Shogren (2008), quantile regression techniques may provide a richer alternative to standard conditional mean regression. This alternative perspective offered by quantile regression is particularly insightful for addressing questions about the determinants of demand among those with low demand who

would be priced out of the market based on a uniform pricing strategy but might be brought into the market via tiered or targeted pricing strategies. While quantile regression characterizes portions of distribution of farmers' WTP away from the mean, ultimately depictions of the full distribution of demand for LLL may be most useful for analyzing and comparing different targeting strategies.

Second, while the conventional 'determinants of demand' approach can provide insights into how different farmers might value LLL differently, it cannot inform targeting strategies as directly as one might think. The problem stems from the fact that it is infeasible to simultaneously target farmers along multiple dimensions. Instead, targeted strategies – whether smart subsidies from a public entity or targeted promotional discounts by a private firm – can only feasibly target one dimension of individual characteristics at a time. Moreover, when the targeted dimension is not inherently categorical (e.g., district of residence) and is instead measured by a continuous variable (e.g., income), such strategies must impose discrete categories (e.g., below the poverty line). These practical realities imply that a *ceteris paribus* analysis, while extremely insightful in some contexts, cannot inform targeting strategies as well as a *mutatis mutandis* approach that ensures that changing the targeted variable triggers associated changes in all other variables. For example, if an LLL provider (with public subsidy incentives) was considering a strategy that targets farmers below the poverty line, they would have to take into account the fact that several other farmer and plot characteristics are correlated with whether a farmer falls in to this poverty category or not. Such farmers are likely to have smaller plots, smaller total land holdings, less education, tighter liquidity constraints, etc. Thus, a *ceteris paribus* coefficient on a dummy variable for 'below the poverty line' in equation (4) potentially misinforms for formulation of segmentation and targeting strategies. Instead, the provider needs to know how demand for LLL among farmers below the poverty line differs *mutatis mutandis* from LLL demand among other farmers.

In order to formulate a *mutatis mutandis* approach, we must look at farmers' WTP from a different angle. To begin with, we can use this data to construct an aggregate demand function as follows:

$$Q(p) = \sum_i \sum_j q_{ij} \times I\left[WTP_{ij} \geq p\right] \tag{5}$$

where $p$ indicates the price of LLL, $q_{ij}$ is the area of plot $j$ held by farmer $i$ and $\mathrm{I}\left[WTP_{ij} \geq p\right]$ is an indicator function that indicates whether farmer $i$ is willing to pay at least $p$ to level plot $j$.[4] This aggregate demand function characterizes the entire distribution of farmers' WTP for LLL, which is particularly useful for exploring deviations from uniform market prices. With a trivial extension, we can construct demand functions for a subset of farmers $M$ who share an observable characteristic:

$$Q_M(p) = \sum_{i \in M} \sum_j q_{ij} \times \mathrm{I}\left[WTP_{ij} \geq p\right] \tag{6}$$

This demand function for segment $M$ is particularly useful for testing different targeting strategies because it characterizes the full distribution of WTP for segment $M$ farmers *mutatis mutandis.* Segment demand curves such as equation (6) also enable standard welfare analysis. Specifically, these curves can generate measures of consumer surplus to evaluate the welfare implications of a given targeting strategy, which consists of a specific price $p_M$ for a defined segment $M$.

$$CS_M = \int_{p_M}^{\infty} Q_M(p)dp \tag{7}$$

These segment-specific consumer surplus measures can be summed to measure overall consumer surplus. This approach can also accommodate situations in which social benefit curves deviate from private demand curves. In the case of LLL, any positive externalities associated with reduced groundwater extraction and reduced diesel fuel consumption could be captured by additional social welfare. Because this additional welfare is a function of the area of land leveled, one can directly incorporate a social benefit curve into a broader social welfare measure that includes the consumer surplus based on private LLL demand.

## 4. RESEARCH SETTING & DATA

Our research setting encompasses the Maharajganj, Gorakhpur, and Deoria districts of EUP. This region is situated in the fertile grounds of the IGP, yet nearly 70% of the 192 million people in Uttar Pradesh live in poverty (Alkire and Santos 2010). During the summer *kharif* growing season, when rice is grown, the

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[4] An alternative to this aggregate demand curve in acreage leveled is an aggregate demand curve that indicates how many farmers adopt LLL, as given by $H(p) = \sum_i \mathrm{I}\left[\sum_j \mathrm{I}\left[WTP_{ij} \geq p\right] > 0\right]$.

southwest monsoons provide much of the water, whereas the wheat crop in the dry *rabi* season relies primarily on irrigation from nearby rivers.

The three districts chosen for this study represent the regional spectrum of productivity in rice-wheat cropping systems. From each district, we randomly selected eight villages, omitting any villages from the sample frame that might have been exposed to LLL from other research or extension activities operating in the area. Only six farmers in our sample reported ever having heard of LLL. Within each village we randomly selected 20-24 farmers from among all those cultivating plots of at least 0.2 acres (the minimum plot size on which to conduct LLL).

In each village, we first obtained a village census for random household selection and convened an information session with these farmers to discuss the mechanics of LLL and its potential benefits and drawbacks. The information session consisted of a short informational video on LLL, the distribution of a picture brochure, and a question and answer session with a non-sample farmer who had previously received LLL services.

We strived to provide complete and objective information without promoting the technology. We informed farmers that recent LLL prices in other parts of India varied between Rs. 400-800 per hour in recent years, but did not reveal any specific price points within this range. During the information session we informed farmers they would have an opportunity to bid on LLL and that the bid options would range from Rs. 250-800 per hour. This price range was printed on the picture brochure for reference. As our second step, we conducted a baseline survey to collect information on the economic activities, demographics and assets of the household, as well as key information about all the plots cultivated or owned by each farmer.

We then held a binding experimental auction in each village to elicit the WTP for LLL. Each farmer was assigned an enumerator to privately guide them through the auction process and record their responses. Since no one else was offering LLL services in this area, the auction was the only way farmers could obtain LLL services on their plots that season. In the auction, each farmer listed up to three plots he or she would most like leveled.[5] For each, the farmer estimated how long it would take to laser level the plot using the amount of time they thought it would take to traditionally level the plot as a benchmark. Enumerators used this estimate to help farmers estimate the total cost of leveling for different prices per

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[5] Most of the farmers in our sample had three or fewer eligible plots (i.e., more than 0.2 acres); 75% had four or fewer eligible plots.

hour of leveling. Then, plot by plot, the enumerator recorded whether or not the farmer was willing to pay for leveling at ten different prices between 250 and 800 Rupees per hour. Once the entire price card was completed, and in the spirit of a Becker-DeGroot-Marschak (1964) mechanism, we revealed the pre-selected binding LLL price (350, 300 or 250 Rs/hour).[6] After three rounds of auctions for candy to familiarize farmers with the auction process, one practice LLL auction was completed before conducting the real one. At the conclusion, enumerators described over 80% of farmers as having understood the experiment very well or fairly well.

Before concluding the auction session, we divided farmers who bid at or above the selected price into treatment and control groups to estimate the impact of LLL on input usage, production and profits. To do this, farmers who stated a WTP for at least one plot at or above the drawn price were included in a 50-50 lottery stratified on maximum WTP to determine who would actually receive the LLL services at this price. We explained to the farmers that the lottery was the only fair way of determining LLL service recipients due to our limited capacity to provide LLL to all those qualifying in the auction. Construction of these treatment and control groups enables us to evaluate the impact of LLL on input usage, yield, and profit, and to estimate network effects on demand for LLL, in subsequent seasons –ongoing dimensions to the broader research project that we briefly discuss later in this paper. Summary statistics on plot and farmer characteristics are given in Table 1, first for the whole sample, then for those who bid at or above the drawn price and those who did not.

Several days after the auction, we administered a detailed baseline survey of our sample farmers. For those farmers who won the lottery to receive LLL services, we coordinated the leveling services with the four LLL providers we contracted to provide these services. A member of our research team accompanied these providers as they leveled the plots of our lottery winners to ensure compliance with the auction outcomes and to collect additional data on leveling time and non-leveling time (i.e., set up and transportation time) required for each plot. These data on LLL costs enable us to capture the cost structure of LLL service providers when testing different targeting strategies.

## 5. LLL DEMAND DETERMINANTS, DEMAND CURVES & COST STRUCTURE

This section presents the empirical methods and results that will enable us to formulate and test specific segmentation and targeting strategies for LLL services. We begin with conventional *ceteris paribus*

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[6] In all but two villages a price of Rs. 250 per hour was selected. In one of the remaining villages we selected Rs. 300 and in the other we selected Rs. 350.

analyses of our experimental auction data, namely, regressions of demand determinants. Since targeted delivery strategies must commit to a single targeting dimension, we must move beyond these determinants and consider *mutatis mutandis* differences in demand distributions along one dimension at a time. We construct these demand distributions as demand curves. Finally, we use data from our LLL providers to characterize the costs associated with leveling.

*Ceteris Paribus Determinants of Demand*

To investigate farm and farmer characteristics that shape demand for LLL, we begin by estimating equation (4). The plot level WTP data and farmer level data in our sample include 63% and 58% zeros, respectively. While a Tobit estimator (Tobin 1958) is often used to deal with a continuous dependent variable with many observations piled up at some limiting level, in this case zero WTP (Cho, et al. 2005; Halstead, et al. 1991; Norris and Batie 1987; Whitehead 2005), it is not appropriate in instances where zero bids do not mask negative bids (Sigelman and Zeng 1999). Because LLL is not a risky technology, and more level plots are unambiguously better than less level plots, we do not believe zero bids mask negative bids. If instead the adoption decision is a two-step process— whether or not to bid, then how much— a hurdle model is more appropriate (Cragg 1971). We therefore estimate (4) using both OLS and a two-step regression model.

For the farm-level characteristics in $\mathbf{z_i}$, we select variables that have been shown in the literature to be associated with technology adoption: age and education of household head, farmer-reported willingness to take agricultural risks, total cultivable land owned, membership in a group or coop, and a factor analytic wealth index.[7] We are not generally as concerned with causality as with association; the policy instrument under investigation is not to change potentially causal variables to increase adoption, but to develop strategies that use observable farm and farmer characteristics to segment the market for subsidization strategies.

For the plot level characteristics in $\mathbf{s_j}$, we include variables likely to affect the input efficiency parameters $\boldsymbol{\varphi}_j^k$ and the overall productivity of the plot. These variables are plot area, whether the plot is upland (not flood-prone) or lowland (flood-prone), time needed to irrigate (per acre), soil type, and the length of time the farmer estimates it will take (per acre) to laser level the plot. The estimated time to

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[7]The factor analytic wealth index employed here consists of total landholdings, thresher hire, combine hire, tractor ownership, large livestock herd size, spending on Diwali or Eid El Kabir festival, monthly mobile phone bill, house condition, participation in MGNREGA public work program, and receipt of migrant remittances.

level variable is the best indicator available to us of how uneven the plot is, and is also indicative of how much the farmer believes she will have to pay in total to level the plot.[8] The main resource LLL is believed to save is irrigation water. Farmers that use rainwater or canal irrigation do not pay for water out of pocket, whereas farmers using pumps (mainly diesel) do. Therefore we include pump use to proxy for the price of pumping, $\omega_i$, and assume other input prices do not vary between farmers. Because LLL offers benefits for several years after leveling we include plot ownership in our regressions.

Under the OLS farmer-level specification, willingness to take risks, total land owned, and group membership are positively associated with WTP under OLS, as well as with the probability of bidding under the two-step specification (see Table 2). These variables are not, however, associated with a higher WTP conditional on a positive bid. The wealth index, on the other hand, comes into play only after conditioning on a positive WTP, with a negative effect. Under OLS specifications, wealth is not shown to affect WTP. Except for the effect of wealth, these findings are generally consistent with other empirical technology adoption studies.

The plot level OLS results (Table 3) indicate that farmers have higher WTP for larger plots than smaller ones, and the two-step regression reveals farmers are more likely to place a positive bid on a larger plot than a smaller one, but that WTP is not increasing in plot size conditional on bidding. Under the OLS specification we find that farmers exhibit greater demand for LLL on plots they own rather than lease, share crop, or rent. The two-step regression results confirm that plot ownership matters also for both the probability of a farmer bidding and large increase in WTP conditional on bidding. Using the two-step regression we also find that conditional on bidding, WTP is increasing with the amount of time per care it takes to irrigate a plot and decreasing in the length of time per acre the farmer estimates it will take to level the plot, conditional on bidding, and amount of time estimated to level has a negative effect on the probability that a farmer bids at all, which makes sense given the direct correlation between expected time to level and expected total cost. We are in the process of extending this *ceteris paribus* analysis of demand determinants with quantile regression in order to more specifically assess the factors that shape the WTP of farmers who are priced out of the market.

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[8] During the information session, farmers were told that the time it takes to laser level a plot is proportionate and similar to the time it takes to traditionally level a plot, so even though farmers were not familiar with LLL they could estimate how long it would take to laser level their plots.

*Mutatis Mutandis Differences in WTP Distributions: Demand Curves*

While these mean comparisons suggest some systematic heterogeneity, the design of the auction also enables us to depict the heterogeneity of LLL demand directly. Figure 1 shows the WTP for different subsets of farmers depicted as demand curves with prices in Rs/hour shown on the y-axis and the corresponding percentage of land each subset of farmers was willing to level on the x-axis. The horizontal line at 500 Rs/hour indicates the approximate current market rate elsewhere in India. Since differences in demand are the crux of any segmentation strategy, we indicate the number of p-values below 10% from pairwise Kolmogorov-Smirnov tests of differences in the underlying WTP distributions for these farmer subsets (e.g., ^^ on the fourth landholding quartile indicates that the WTP distribution for this quartile is pairwise different than two other landholding quartiles with p<0.10).

The demand curves in figure 1 are very elastic below the market price of 500 Rs/hour, which implies that subsidies could dramatically expand LLL adoption. Less than 5% of the land covered by our sample in any district would be leveled at the market price, but nearly 50% would be leveled at half that price. These graphs indicate potentially useful dimensions of demand heterogeneity. Along most dimensions, most of the demand heterogeneity occurs below the uniform market price, which further implies that segmentation strategies that lower prices for some farmer subsets might be promising. There are some pronounced demand differences by district and caste. Nearly half of our sample farmers carry an official below-poverty-line (BPL) card, which could be a straightforward segmentation approach. Surprisingly, however, those with BPL cards are willing to level more than those without at nearly every price. In the bottom three panels of figure 1, we disaggregate farmers by different quantile dimensions. In all three dimensions, there are few if any demand differences at the market price, but significant differences below this price. Farmers in the lowest total landholding quartile demand twice as much land (in percentage terms) laser leveled at 450 Rs/hour than the other quartiles. Plot size differences are more systematic, with the highest quartile having the highest LLL demand below the market price. Finally, differences in demand by credit access[9] suggest that liquidity constraints may have constrained LLL demand: farmers with no self-reported access to credit (first quartile) demand less LLL at every price below the market price than farmers who in a pinch could get a loan of Rs. 20,000 or more (third and fourth quartiles). While credit access is not a potential segmentation dimension per se, these differences do suggest that relieving liquidity constraints with microfinancing for LLL might be worth exploring as part of any dissemination strategy. As a methodological note, even though characterizing demand just

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[9] Farmers were asked how big of a loan they could get if they had to quickly raise money for an opportunity or obligation.

below a market price is essential to any subsidy or segmentation strategy, it is difficult to learn much about demand in this price region from market outcomes since these individuals are typically priced out. In this case, experimental auctions can be especially insightful.

Since price elasticity of demand for LLL below the market price is relevant to the formulation of segmentation or subsidy strategies, we compute simple arc elasticities using the auction data. Specifically, we calculate how a 20% price reduction from 500 to 400 Rs/hour changes the area that farmers want to laser level. For our full sample, this arc elasticity is 6.3, indicating very elastic demand for LLL just below the prevailing market price. LLL demand elasticity is highest in Gorakhpur district (7) and lowest in Deoria (5.9). To compare price sensitivity across the wealth distribution, we compute arc elasticities for each quartile for 10%, 20%, and 30% price reductions from the market price. For each reduction level, the highest wealth quartile is most responsive to price, but LLL demand among the lowest wealth quartile is still quite elastic. Furthermore, these quartile differences are less pronounced for bigger price reductions.

*LLL Cost Structure*

As mentioned above, the dominant pricing strategy for LLL custom hire service providers is to charge farmers a fixed rate for the leveling time required to level a given plot. In order to accurately test novel delivery strategies, we must understand the cost structure behind this simple price per hour model. This is particularly true since the kinds of strategies we want to explore aim to bring farmers into LLL who might otherwise be priced out of the market – and these farmers are likely to be quite different than those whose demand for LLL services has supported the emergence of this dominant pricing model. Any new business or delivery models must therefore reflect the actual cost structure of LLL custom hire services. At the time our contracted LLL providers leveled the plots from the auction, a member of our team collected detailed data on leveling and non-leveling time. We have since compiled the other cost data needed to characterize the cost structure of LLL providers.

For the purposes of this analysis, we are most interested in the cost of leveling the plots in our sample. Based on this cost per plot, we can compute how different targeting strategies affect the net returns of LLL providers. Because we only have provider cost data for plots that were actually laser leveled after the auction, we must impute costs for the other plots in our sample. To do this we matcheach non laser leveled plot to a similar laser leveled plot. Using factor analysis we assign a score to each plot in our sample for which WTP is positive; plots for which WTP is zero will not be leveled under any potential market segmentation strategy. For factor analysis, we use plot area, farmer landholdings, farmer age, whether a plot is upland or lowland, and farmer WTP to level the plot. Using these scores, we

calculate the distance in 'plot characteristic space' between any two plots in the same village pair. We impute leveling, travel, and set-up costs from the nearest leveled plot for each unleveled plot. We anticipate leveling many more plots after the second round of auctions which will drastically reduce or eliminate the need for this type of matching in future analysis.

## 6. FORMULATING & TESTING SEGMENTATION STRATEGIES

In this section, we formulate a few segmentation strategies according to specific objectives and the heterogeneity that is apparent from the analysis above. These strategies are formulated so they are comparable in their 'external' cost (e.g., subsidy cost) and evaluated based on their cost effectiveness in bringing additional acres and farmers into LLL. Using the cost analysis described above, we can also evaluate the strategies according to how they change the net returns to private LLL providers. We begin with the status quo: a uniform market price. We then move to hybrid strategies that use a combination of subsidies and targeting to fuel LLL diffusion. We use current subsidies on outright purchases of LLL machinery as a benchmark for current public support for LLL.

*Targeting Objectives & Strategies*

State-level governments in India offer many subsidies intended to increase agricultural production. Many states have recently introduced or are considering subsidies on the purchase of new LLL equipment. The most common level of subsidy support for this equipment would translate roughly into an effective hourly subsidy of Rs. 50 in EUP. We take this level of near-term public support for LLL as a benchmark and derive and test targeted strategies that are comparable in total public cost to this apparently realistic subsidy level.

We consider two different targeting objectives. First, if one is primarily concerned about excessive groundwater extraction (and possibly diesel fuel consumption for pumping this groundwater), the primary objective of any targeted strategy should be to increase the land area that is leveled – especially in areas where groundwater extraction is high relative to recharge rates. Since the severity of the groundwater extraction problem does not change much across our sample, we reduce this objective simply to increasing the total area that is leveled. Second, if one is primarily concerned about the welfare and profitability of small-scale and generally poorer farmers, the primary objective of targeted strategies should be to increase the number of farmers who level their plots. In a dynamic sense, these two objectives are interrelated since increasing the number of households adopting the technology might increase the rate at which LLL diffuses across the landscape. For now, we focus mainly on the second

objective and formulate strategies that tend to progressively price LLL to favor relatively poorer farmers with smaller landholdings. We can then test how effectively these strategies might achieve the first objective as well.

To demonstrate how demand analysis can be used to inform market segmentation strategies, we simulate LLL uptake in our sample using several candidate subsidy and segmentation plans. These plans include a uniform subsidy of 50 Rs/hour on LLL custom hire rates and five targeting strategies informed by our demand analysis. From figure 1 it is apparent that subsidization in general could increase the rate of diffusion of LLL. Proper market segmentation could make subsidies even more efficient by targeting particular types of farmers according to their price sensitivity. Here we compare the performance of five market segmentation strategies against uniform subsidies and each other.

**Geographic targeting by district**: Since LLL services are rendered directly to a given immobile plot, geographic segmentation is perhaps the easiest departure from uniform pricing to envision. Under this strategy, service providers would charge different prices in separate districts depending on demand for LLL. Arbitrage and leakage are insignificant concerns with this strategy since plots are immobile. While there are some demand differences between the three districts in our sample, the three districts are relatively similar in many regards, which limits the potential for welfare gains from this strategy. We experiment with a strategy that offers a 100 Rs/hour subsidy to Deoria district and no subsidy to the other two of our sample districts.

**Wealth targeting based on poverty status:** Although segmenting by wealth is a popular strategy in theory, implementation may be challenging. One option for segmenting markets in this way is to offer vouchers to those with BPL cards, but note that figure 1 suggests that those above the poverty line might need more (not less) encouragement to level their plots. Although it is possible to formulate pure BPL subsidies, in order to ensure cost comparability we opt for a hybrid offers different BPL subsidies by district: 100 Rs/hour BPL subsidy for Gorakhpur and Maharajganj districts and 150 Rs/hour BPL subsidy for Deoria district.

**Caste targeting:** Caste remains a popular dimension for targeting social programs in India. We find some evidence for systematic differences in LLL demand between lower caste and general caste farmers in our sample. We experiment with a simple caste targeting strategy that offers lower caste farmers a 100 Rs/hour subsidy for LLL.

**Landholdings segmentation**: Although a broad wealth index might make sense as a segmentation dimension, total landholdings are easier to observe and, therefore, easier to implement. Furthermore, there are non-wealth reasons for demand for LLL and other agricultural technologies being higher for farmers with more land, such as the ability to experiment or manage risk (Feder 1980). We experiment with a subsidy of 150 Rs/hour for farmers in the first quartile of the landholdings distribution.

**Plot size segmentation**: Explicitly segmenting on plot size could involve offering vouchers for plots that are viable for LLL but below a given threshold. This strategy would be less prone to underreporting than segmentation by total landholdings and, based on figure 1, potentially effective given systematic demand heterogeneity below the market price. We experiment with a strategy that offers a 150 Rs/hour subsidy for the first quartile of plot size and a 50 Rs/hour subsidy for the second and third quartile of plot size.

*Testing Segmentation Strategies*

Soon, we will have detailed data on heterogeneous benefits from LLL and costs of LLL provision, which will enable us to evaluate market segmentation strategies in terms of how much water, diesel, and other inputs they save or how they increase production and profitability. For now, we evaluate the targeting strategies above using the following metrics: (i) total acreage in the sample under LLL, (ii) total number of farmers adopting LLL, (iii) cost effectiveness of bringing additional acres and farmers into LLL (subsidy cost per additional acre or farmer), and (iv) consumer surplus-based measures of welfare and welfare efficiency.

Table 4 summarizes the different targeting strategies we test and includes the percentage of farmers and acres in our sample that are brought 'into' LLL. Figure 2 shows how these strategies compare in the total acreage leveled. The top panel includes 90% confidence intervals on this simulation result based on bootstrapping. The middle and bottom panels depict the distribution of these leveled acres across poverty status (farmers with and without BPL cards) and caste. Figure 3 depicts the cost effectiveness of these targeting strategies as a function of total subsidy cost and represents the net gain or loss to LLL providers associated with each strategy.

As the final step in this *mutatis mutandis* approach, we use a welfare framework to estimate consumer surplus by segment as in equation (7), where the segments correspond to the targeting dimension for each strategy. As with the estimate acres in LLL, we bootstrap these consumer surplus calculations to generate confidence intervals. Figure 4 shows the results for this welfare metric, both overall and broken down by BPL and caste.

A subsidization scheme must first to be feasible to implement in practice. Segmenting on wealth would not be a good candidate since there is some subjectivity in determining the factors in a wealth index and, even if a good index could be used, it would be difficult to measure at the household level for each farmer in the LLL market. On the other hand, segmenting on ownership of a BPL card would be a more feasible option since this is relatively easy to verify. Other observable variables such as caste or total landholdings that are highly correlated with wealth would also easier to segment on than a multi-dimensional wealth index.

Secondly, there may be equity-efficiency tradeoffs when choosing the criteria on which to segment. Balancing these two objectives might require that higher quantiles do not receive a subsidy that is greater than that of farmers at lower quartiles. For example, in practice it would be hard to justify giving those above the poverty line a higher subsidy for LLL than those below, even if such a subsidy results in more land coming under LLL. Thirdly, we should consider the producer costs alongside farmer benefits for each strategy. For private LLL providers to buy into any targeted subsidy scheme, the transfer they receive from the government must be high enough to offset their costs, which vary by targeting strategy.

We use our demand curves to simulate changes in consumer surplus and additional acreage leveled for segments of the population due to each strategy. These results are shown in Table 5 and represented graphically in Figure 2 and figure 4. The top panel in Figure 2 compares the total acres that would be leveled in our sample under each segmentation strategy. The 'Market' strategy is our baseline case where no intervention is made. In this case 4% of farmers adopt LLL, and only 3% of all sample land is laser leveled. The total amount of consumer surplus generated is Rs. 3,200 and the net revenue earned by the provider is Rs. 660. Currently the government provides subsidies on equipment purchases by LLL providers. At current rates of subsidization we calculate that a 50 Rs/hour subsidy could be passed on uniformly to consumers. With this uniform 50 Rs/hour subsidy 6% of farmers adopt LLL and 4.5% of sample land is laser leveled. Consumer surplus would increase to Rs. 6,500. The uniform subsidy would come at a cost of Rs. 5,550 and require minimal effort for implementation. However, the service provider would earn Rs. 4,050 in net revenue for providing the service demanded under the uniform subsidy factoring in the transfer.

Moving away from a uniform subsidy strategy to targeted one allows us to take advantage of market heterogeneity to increase adoption, particularly among poorer segments of the population. We do not include the cost of implementation in our simulations, but recognize that each of these strategies would incur implementation costs in practice and (on most cases) offer farmers opportunities to cheat the

system. A district level segmentation scheme would be the easiest to implement, and would not be vulnerable to farmers cheating the system. Offering a 100 Rs/hour subsidy to sample farmers in Deoria district only would cost Rs. 6,240, about 13% more than the uniform subsidy. This strategy would result in 6.3% of households adopting LLL, 5.2% of sample land coming under LLL, and Rs. 9,000 of consumer surplus. While easy to implement, the strategy is not very effective at increasing LLL adoption. This strategy would be, however, appealing to LLL providers. They would receive Rs, 6,600 in net revenue after receiving the transfer. A strategy that combines district level segmentation with segmentation based on poverty status (100 Rs/hour for BPL card holders in Gorakhpur district and 150 Rs/hour for BPL holders elsewhere) fares slightly better in increasing adoption, although segmenting on BPL card would incur additional implementation costs and opportunity for cheating. This hybrid plan costs Rs. 6,000 and results in 8.3% of household adopting land on 6% of the total sample acreage— a large improvement in both dimensions over the uniform subsidy—and result in Rs. 9,000 of consumer surplus. However, this strategy would not appeal to providers, who would stand to lose Rs. 2,900 in net revenue after receiving the transfer. Moving from a district-level segmentation strategy to a hybrid district and poverty status segmentation strategy has equity implications: Under the district strategy two-thirds of the consumer surplus is enjoyed by lower caste members and one-half by those holding BPL cards. Under the district-poverty status hybrid, lower case members enjoy 80% of the consumer surplus and BPL card holders enjoy nearly 90%.

A caste-level segmentation strategy where lower caste members receive a 100 Rs/hour subsidy costs Rs. 6,000—slightly less than the district-poverty status hybrid—but results in slightly more LLL adoption in terms of percent of adopting household (8.5%) or percent of land under LLL (6.3%). The total consumer surplus generated, however, is slightly less at Rs. 8,000. The consumer surplus is divided in a similar fashion between upper and lower caste members, and between BPL card holders and non-BPL cardholders, as the hybrid district-poverty status strategy. Segmenting on caste, however, is less appealing to service providers that the hybrid district-poverty status strategy; they would lose Rs. 4,000 in net revenue after receiving the transfer. Segmenting on total landholdings increases adoption and consumer surplus similarly to the caste segmentation strategy. This strategy is even less appealing to service providers, who would lose Rs, 5,230 in net revenue after receiving the transfer.

These simulation results using data from an experimental auction and from producer cost reports sheds some light on how different segmentation strategies can be used to achieve different goals such as increasing the number of households adopting a new technology, increasing the number of acres under a new technology, or increasing total consumer welfare. Furthermore, because we have data on farmers' caste and poverty status, we can examine to what extent different segmentation strategies are pro-poor. In

ongoing research we are expanding our analysis to include water and other input savings. If savings are heterogeneous then policies can be designed to target the land on which LLL will result in the greatest input efficiency gains. We are also developing dynamic simulations that account for first generation adoption to increase demand for a technology in future seasons through social networks.

## 7. CONCLUSION

In this analysis, we argue that experimental auctions are a useful tool for informing the design and evaluation of alternative market segmentation and subsidy strategies. The mix of public benefits and heterogeneous private benefits associated with LLL in eastern Uttar Pradesh, India makes these strategies particularly potent as a means of improving social welfare. Our analysis of farmers' demand for LLL showcases their heterogeneity of valuation for this technology. Specifically, among those who would be priced out of a uniform-price-based LLL market we find marked demand differences by district, wealth, caste, landholding, and plot size. Simple arc elasticities suggest considerable price sensitivity just below the market price for all farmer types. Simulations show how it is possible to draw more land under LLL at a lower cost by segmenting markets by observable characteristics across which technology demand differs. Demand differences by credit access suggest that liquidity constraints may affect LLL uptake and that bundling segmentation strategies with credit might further encourage uptake. Although further work is needed, this preliminary analysis demonstrates how experimental auctions can improve our understanding demand heterogeneity and its underlying determinants and how this, in turn, can inform novel segmentation and subsidy strategies.

In ongoing work, we extend our analysis to address several related issues. First, we evaluate the impacts of LLL on input use, yields, and profitability among farmers. We do this by drawing on household- and plot-level data from successive intra-seasonal survey rounds of households that were part of the randomized control trial of LLL that was integrated into the experimental auction design through a post-auction lottery. These findings will enable us to explore more precisely the private and public benefits of different segmentation and subsidy strategies. Second, there are more rigorous ways to formulate targeting strategies based on the metrics we currently use. For example, we are exploring optimization routines that would take into account the subsidy cost and LLL providers' costs simultaneously. These routines would then choose a targeting strategy along a given dimension that maximizes consumer surplus while satisfying a zero profit constraint for LLL providers. Finally, we extend these results to help address policy challenges faced by both public policy-makers and corporate decision-makers in South Asia. Specifically, we provide recommendations on the tradeoffs and scenarios by which a resource-conserving technology such as LLL can be promoted among small-scale, resource-

poor farmers through partnership mechanisms that leverage resources from both the public and private sectors.

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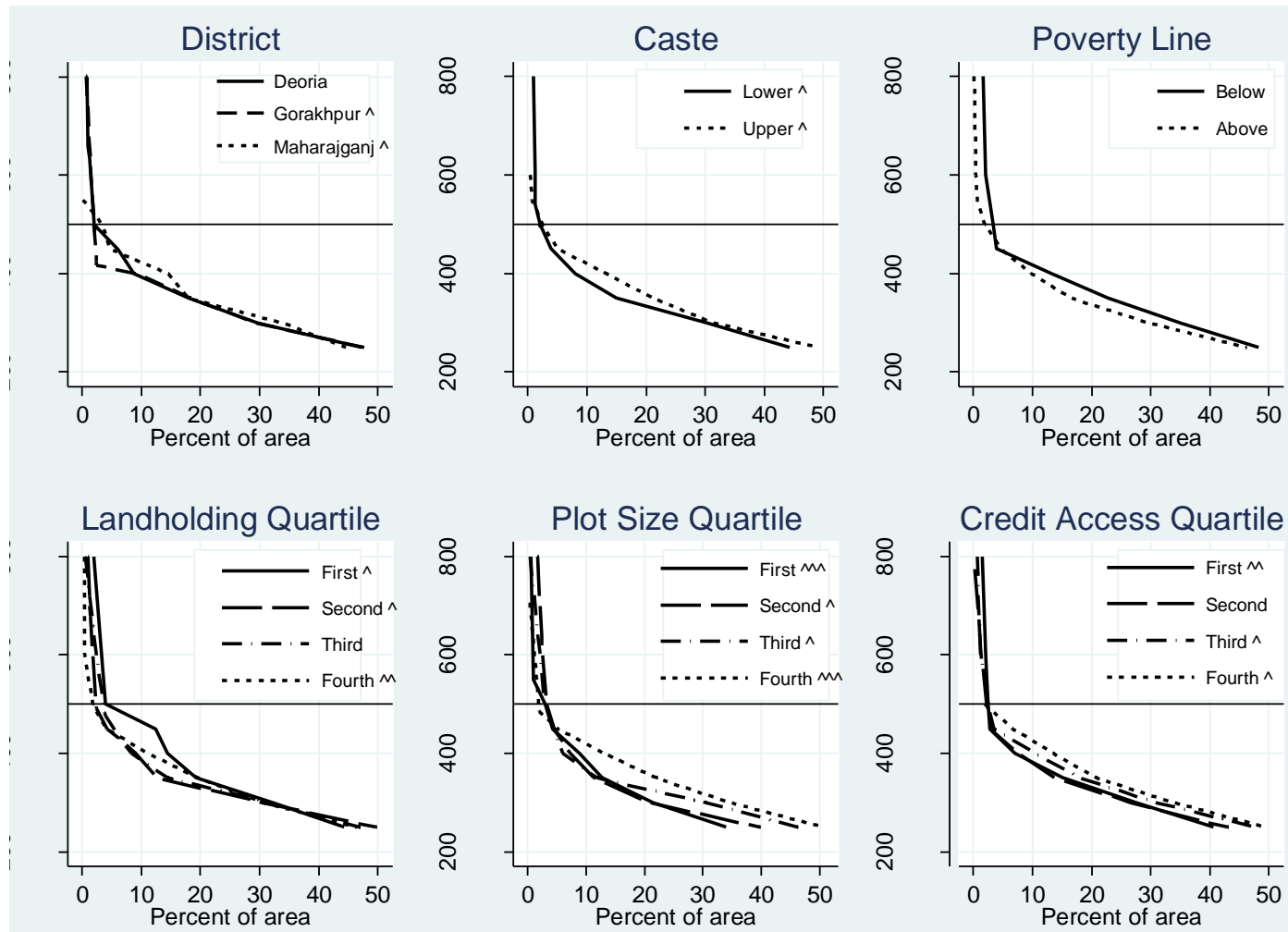**Figure 1.** Disaggregated demand curves for LLL (WTP in Rs./hour on y-axis; ^, ^^ and ^^^ indicate the number of significantly different pairwise Kolmogorov-Smirnov comparisons of the underlying WTP distributions at the 10% level)

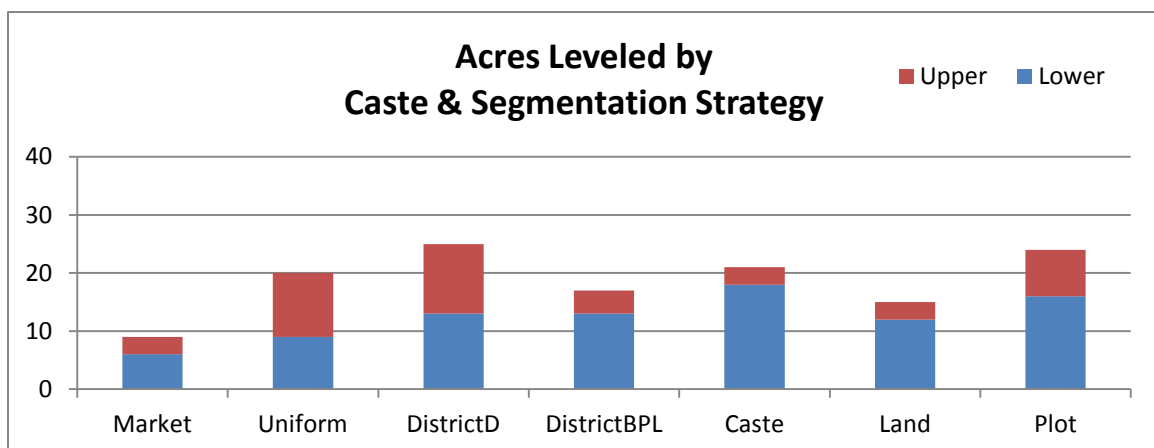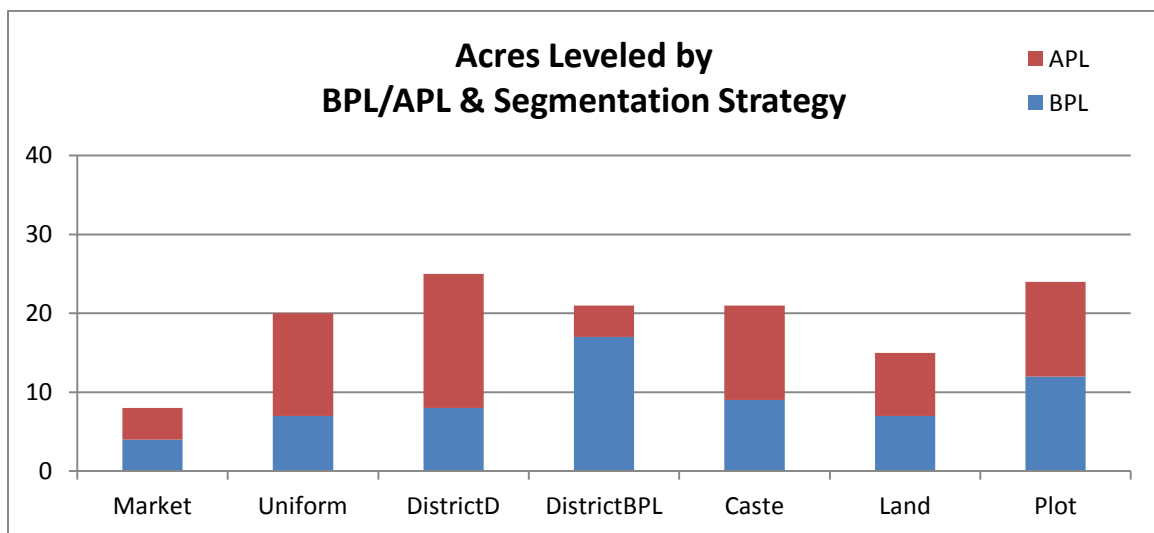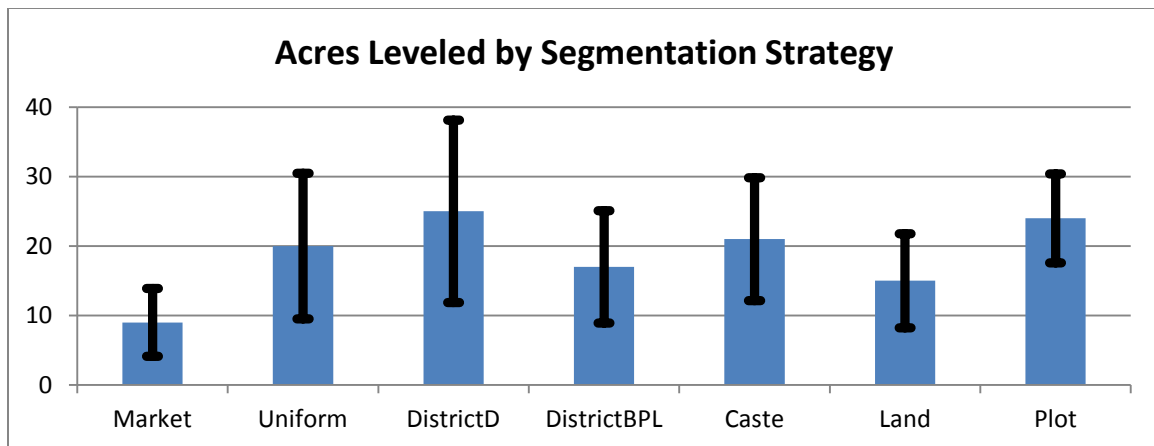**Figure 2.** Simulated Acreage Leveled by Segmentation Strategy
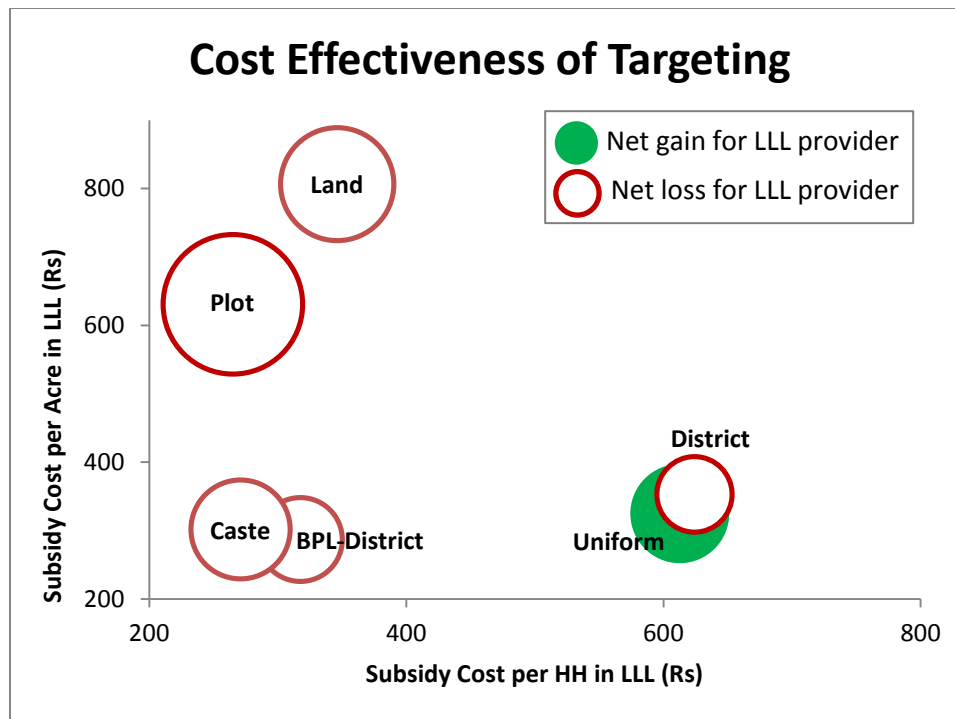
**Figure 3** Cost effectiveness of various targeting strategies with change in net returns to private LLL provider indicated as bubbles.
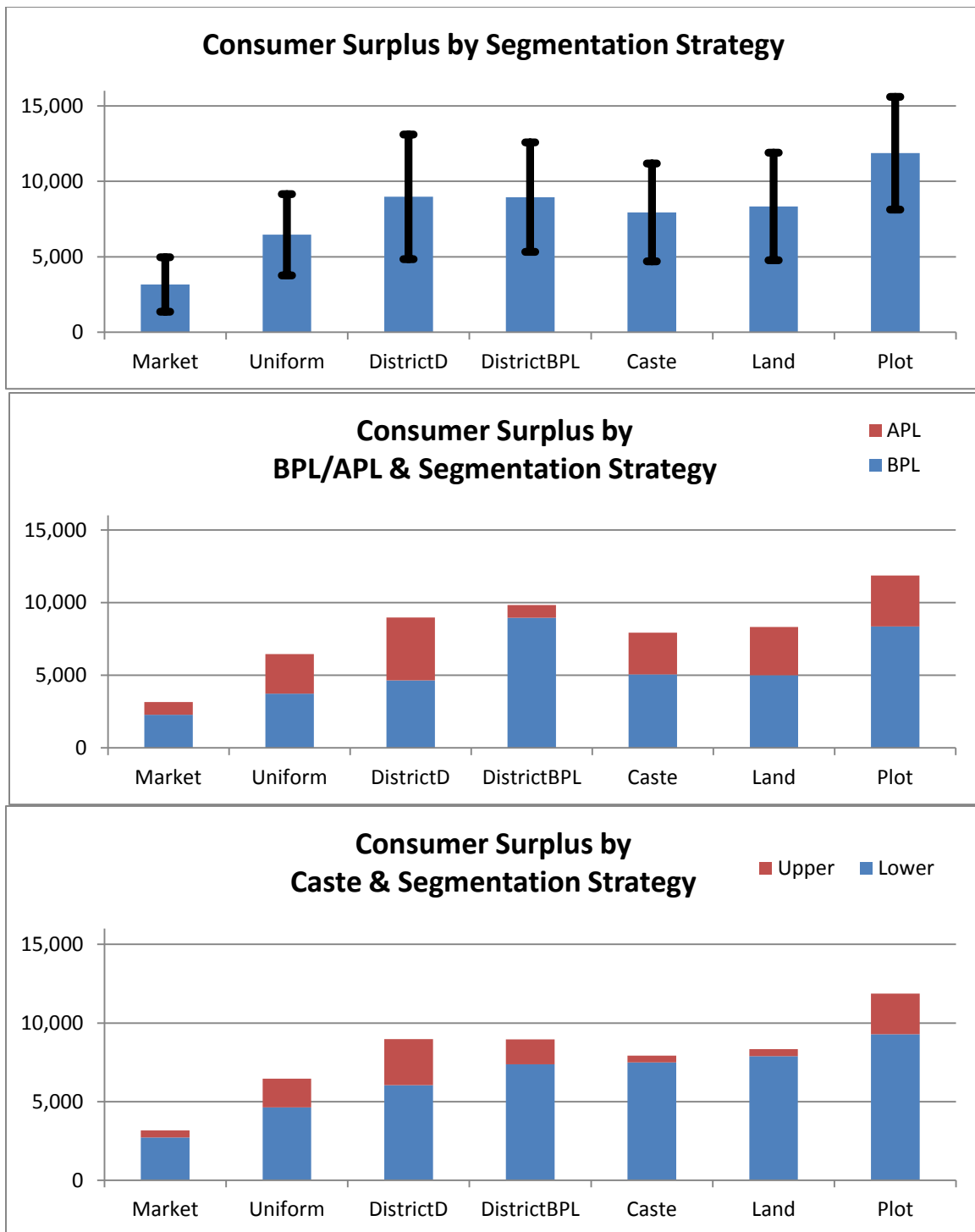
**Figure 4** Consumer surplus by targeting strategy with 90% confidence intervals depicted (top panel) and distribution of consumer surplus by below poverty line (BPL) (middle) and caste (bottom).

**Table 1.** Means (Standard Deviation) for Selected Variables for the Full Sample and for Three Sub-samples from the Experimental LLL Auction

| | Full Sample (N=478) | | WTP < price[a] (N=192) | | WTP ≥ price (N=286) | |
|---|---|---|---|---|---|---|
| Age of HH head | 50.09 | (15) | 49.11 | (14.8) | 50.87 | (15.1) |
| Male HH head | 0.82 | (0.38) | 0.76***[b] | (0.43) | 0.87 | (0.34) |
| Education of HH head (years) | 6.27 | (5.51) | 5.6** | (5.37) | 6.78 | (5.56) |
| HHs in upper caste | 0.22 | (0.42) | 0.16*** | (0.37) | 0.27 | (0.44) |
| Wealth Index[c] | 0.50 | (0.29) | 0.48 | (0.28) | 0.52 | (0.29) |
| BPL card holder | 0.47 | (0.50) | 0.50 | (0.50) | 0.46 | (0.50) |
| Willingness to take risks (1=unwilling, 7=willing) | 4.55 | (1.51) | 4.25*** | (1.59) | 4.78 | (1.39) |
| Area Owned (acres) | 2.06 | (4.29) | 1.62** | (5.02) | 2.42 | (3.58) |
| Plot Size (acres) | 0.72 | (1.11) | 0.50*** | (0.69) | 0.88 | (1.31) |

[a]Indicates the final binding price in the auction. [b]Test of nonzero difference in means between WTP < price and WTP ≥ price (***$p < .01$, **$p < .05$, *$p < .10$). [c]Factor analytic index that includes a livestock index, amount spent on Diwali, monthly phone bill, condition of house, household participation in MGNREGA, domestic and international remittances, whether farmers custom-hired a thresher combine, and whether households owned a tractor.

**Table 2** Farmer-level determinants of maximum WTP for LLL

| Dependent variable | OLS | Two-step | |
| --- | --- | --- | --- |
| | WTP | WTP >0 | WTP |
| Education of household head (years) | 2.641 | 0.015 | 0.752 |
| | (1.648) | (0.014) | (1.042) |
| Age of household head | 0.4 | 0.006 | -0.418 |
| | (0.509) | (0.004) | (0.33) |
| Willingness to take risk (5 point scale) | 18.228*** | 0.156*** | 0.158 |
| | (5.785) | (0.047) | (4.239) |
| Maximum amount of credit farmer could obtain | 0.335 | 0.001 | 0.205 |
| | (0.291) | (0.002) | (0.217) |
| Total area owned | 4.510*** | 0.131*** | 0.291 |
| | (1.266) | (0.049) | (0.845) |
| Group or co-op member (0,1) | 56.382** | 0.439* | 25.577 |
| | (27.814) | (0.241) | (20.815) |
| General caste member (0,1) | 9.098 | 0.033 | 2.171 |
| | (21.502) | (0.199) | (13.703) |
| Wealth index | -7.306 | 0.037 | -17.779** |
| | (12.751) | (0.121) | (8.88) |
| Constant | 50.561 | -1.028*** | 322.452*** |
| | (41.596) | (0.344) | (31.953) |
| Sigma | | | 92.729*** |
| | | | (9.496) |
| Observations | 455 | 455 | 292 |
| R-squared | 0.084 | 0.0835 | |

Robust standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Wealth Index includes a livestock index, amount spent on Diwali, monthly phone bill, condition of house, household participation in MNREGA, domestic and international remittances, whether farmers custom-hired thresher combine, and whether households owned a tractor.

**Table 3.** Plot-level determinants of WTP for LLL

| Dependent variable | OLS WTP | Two-step WTP >0 | WTP\|WTP>0 |
|---|---|---|---|
| Plot area | 4.259** | 0.052* | -1.083 |
| | (1.88) | (0.03) | (0.905) |
| Upland plot | -14.224 | -0.1 | -7.776 |
| | (14.721) | (0.109) | (12.03) |
| Owner operated | 77.829*** | 0.594** | 45.023*** |
| | (21.774) | (0.257) | (10.926) |
| Irrigation time | 0.017 | 0 | 0.026* |
| | (0.014) | (0) | (0.014) |
| Pump as primary irrigation source | 16.986 | 0.124 | 1.538 |
| | (16.892) | (0.139) | (10.989) |
| Estimated time to level | -13.706*** | -0.107** | -3.057 |
| | (4.379) | (0.045) | (3.413) |
| Constant | 103.547* | -0.471 | 285.923*** |
| | (58.144) | (0.48) | (44.774) |
| Sigma | | | 92.887*** |
| | | | (7.314) |
| Observations | 1,054 | 1,054 | 460 |
| R-squared | 0.028 | 0.0275 | |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Results for soil type are jointly significant but not reported.

**Table 4** Summary of targeting strategies

| | Description | Subsidy Cost (1,000 Rs) | Provider Cost (1,000 Rs) | Farmers in LLL (%) | Acres in LLL (%) |
|---|---|---|---|---|---|
| **Market** | 500 Rs/hour uniform market price | 0 | 247.3 | 4.0% | 3.0% |
| **Uniform Subisdy** | 50 Rs/hour uniform subsidy (effective subsidy of LLL equipment subsidy) | 55.1 | 510.9 | 6.0% | 4.5% |
| **District** | 100 Rs/hour subsidy in Deoria district | 62.4 | 474.4 | 6.3% | 5.2% |
| **Below Poverty Line (BPL)-District** | 100 Rs/hour subsidy for farmers with BPL card in Gorakhpur and Maharajganj districts; 150 Rs/hour BPL subsidy in Deoria | 60.3 | 475.4 | 8.3% | 6.0% |
| **Caste** | 100 Rs/hour subsidy for lower caste farmers | 54.2 | 481.4 | 8.5% | 6.3% |
| **Land** | 150 Rs/hour subsidy for farmers in lowest landholding quartile | 51.9 | 442.4 | 7.4% | 5.3% |
| **Plot** | 150 Rs/hour subsidy for farmers in lowest plot size | 58.3 | 496.4 | 8.9% | 6.2% |

**Table 5.** Acreage and Consumer Surplus by Segmentation Strategy and Societal Group

| Strategy | Total Acres | By Caste Lower | By Caste Upper | By BPL status BPL | By BPL status Non-BPL | % of Total Acres by Group Lower | % of Total Acres by Group Upper | % of Total Acres by Group BPL | % of Total Acres by Group Non-BPL |
|---|---|---|---|---|---|---|---|---|---|
| Market | 9 | 6 | 3 | 4 | 4 | 67 | 33 | 44 | 44 |
| Uniform | 20 | 9 | 11 | 7 | 13 | 45 | 55 | 35 | 65 |
| District | 25 | 13 | 12 | 8 | 17 | 52 | 48 | 32 | 68 |
| District-BPL | 17 | 13 | 4 | 17 | 0 | 76 | 24 | 100 | 0 |
| Caste | 21 | 18 | 3 | 9 | 12 | 86 | 14 | 43 | 57 |
| Land | 15 | 12 | 3 | 7 | 8 | 80 | 20 | 47 | 53 |
| Plot | 24 | 16 | 8 | 12 | 12 | 67 | 33 | 50 | 50 |

| Strategy | Total CS | By upper / lower caste Lower | By upper / lower caste Upper | By BPL status BPL | By BPL status Non-BPL | % of Total CS by Group Lower | % of Total CS by Group Upper | % of Total CS by Group BPL | % of Total CS by Group Non-BPL |
|---|---|---|---|---|---|---|---|---|---|
| Market | 3,163 | 2,719 | 444 | 2,281 | 881 | 86 | 14 | 72 | 28 |
| Uniform | 6,463 | 4,640 | 1,823 | 3,740 | 2,723 | 72 | 28 | 58 | 42 |
| District | 8,973 | 6,046 | 2,927 | 4,652 | 4,321 | 67 | 33 | 52 | 48 |
| District-BPL | 8,952 | 7,377 | 1,575 | 8,952 | 0 | 82 | 18 | 100 | 0 |
| Caste | 7,931 | 7,488 | 444 | 5,056 | 2,875 | 94 | 6 | 64 | 36 |
| Land | 8,331 | 7,887 | 444 | 5,012 | 3,319 | 95 | 5 | 60 | 40 |
| Plot | 11,864 | 9,291 | 2,573 | 8,354 | 3,510 | 78 | 22 | 70 | 30 |