Targeting Technology to Increase Smallholder Profits and Conserve Resources: Experimental Provision of Laser Land-Leveling Services to Indian Farmers

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I. Introduction

For most of the rural poor in many 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 and extension in many of these settings, the dissemination of new agricultural techniques and technologies may be increasingly shaped by the private sector (Feder, Willett, and Zijp 2001). When the private agroservices sector thrives, farmers often benefit from better information, more options, and, ultimately, enhanced productivity. For many agricultural technologies, however, the private sector lacks the incentives and information needed to successfully serve the needs of small-

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scale, 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 sectors (Jack 2013a). Consequently, even when there is a political or private-sector willingness to cater to poor farmers, a vague and incomplete understanding of the various values that different farmers place on a technology often prevents these support mechanisms from translating into agricultural-productivity gains for the poor. Motivated by this void, we use experimental methods to characterize farmers' heterogeneous demand for, and benefits from, a new agricultural technology in eastern Uttar Pradesh (EUP), India, in order to inform segmentation and targeting strategies. As the crux of our approach—and a methodological contribution of this work—we integrate a binding experimental auction with a randomized control trial (RCT) in order to rigorously assess heterogeneity in both valuation and impact.

Farmers in the rice-wheat systems of this region of the Indo-Gangetic Plain (IGP) typically flood-irrigate their fields, using water extracted from tube wells by diesel pumps. To ensure that his or her plot is completely irrigated, each farmer must flood the plot to its highest point. Consequently, relatively small undulations in seemingly flat plots can increase the amount of water required to irrigate by up to 25%, leading to inefficient use of fertilizers and chemicals, increased biotic and abiotic stress, and lower yields (Jat et al. 2006, 2009). To reduce pumping costs and thereby improve profitability, farmers have devised rudimentary techniques to level their plots (e.g., dragging wooden beams behind draft animals or tractors) with a precision of ±5 cm.[1] Laser land leveling (LLL), an unfamiliar technology in our study area, uses a fixed laser emitter and a laser receiver mounted on an adjustable drag scraper to level plots with a precision of ±1–2 cm. Though clearly more sophisticated than traditional leveling techniques, LLL uses relatively basic equipment, requires minimal training, and is available in other areas of the IGP, generally as a custom-hire service at a flat hourly rate. Because farmers are keenly aware of how important it is that their plots be level and well versed in traditional leveling techniques, they can generally size up plot-specific prospective benefits from LLL quite readily: leveling is leveling—LLL just does it better.

[1] Under most circumstances, Indian farmers do not pay for water directly, but they do pay for diesel fuel and therefore face strong incentives to reduce pumping time.

LLL trial results from the western IGP have found large and statistically significant irrigation savings on the order of 10%–30% (Jat et al. 2006, 2009). While it is tempting to extrapolate these LLL trial results to the broader IGP and beyond, substantial differences in average farm and plot size, poverty rates, and access to other technologies and infrastructure imply that results from controlled trials may bear little resemblance to on-farm experiences. These differences have important implications for farmers' valuation of the technology and service providers' incentives to expand into poorer regions like our study area in EUP. LLL may also generate important, though difficult to document, public benefits in the form of reduced groundwater depletion, chemical input use, diesel fuel consumption, and greenhouse gas emissions. In the case of groundwater depletion (Mukherji 2007; Shah 2007), even small reductions in pumping across a large population can cause water tables to rise, reduce pumping costs more broadly, and improve the sustainable use of groundwater for communities that share these resources. The expansion of wells and pumps in recent decades has dramatically increased groundwater depletion in northern India in particular, a region where access to groundwater can shape poverty and fuel local conflicts (Sekhri 2014).[2] Combined with potentially significant but heterogeneous private benefits, these public benefits make novel market segmentation strategies and targeted subsidies particularly potent as a means of improving social welfare.

In order to formulate targeting strategies, it is first necessary to understand how demand for LLL varies spatially and across different types of farmers and farms. Such heterogeneous demand can arise because benefits of the technology vary across locations and individuals (Suri 2011) or because nonprice barriers to adoption are heterogeneous. Consequently, demand can be shaped by a variety of farm and farmer characteristics, such as farm size, soil and climate characteristics, 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 to designing market segmentation or targeted subsidization strategies. Such targeted subsidies can yield efficiency gains over uniform subsidies that do not reflect differences in benefits or adoption constraints.

Fueled by these potential gains, the literature on targeted subsidies has grown in recent years, including comparisons of untargeted to targeted fertil-

[2] While the vast majority of these wells and pumps are private, explicit and implicit subsidies encourage these investments. Some of the wells are directly financed by public funds or nongovernmental organizations and available for communal use. Sekhri (2011) shows that the presence of public wells can reduce farmer investments in private wells and thereby reduce overall groundwater extraction.

izer subsidies in Malawi (Ricker-Gilbert, Jayne, and Chirwa 2011), evaluations of micro-ordeals designed to screen recipients of health-product subsidies on the basis of likelihood of use in Kenya and China (Ma et al. 2013; Dupas 2014), and comparisons of alternative means of targeting cash transfers in Indonesia, including community targeting, where community members rank each other in terms of need (Alatas et al. 2012). A converging thread of literature is developing around the use of experimental markets to understand consumer valuation of food traits in developed countries (Hayes et al. 1995; Melton et al. 1996; Alfnes and Rickertsen 2003) and household valuation of health and nutrition products such as bed nets, fortified foods, high-quality foods, and infant foods of certified quality in developing countries (Masters and Sanogo 2002; Hoffmann, Barrett, and Just 2009; De Groote, Kimenju, and Morawetz 2011; Demont et al. 2013; Dupas 2014).

At the confluence of the research on targeted subsidies and that on experimental auctions is work that evaluates the cost-effectiveness of using reverse auctions to allocate land-use subsidies in Malawi (Jack 2013b) and ecosystem service contracts in Indonesia (Jack, Leimona, and Ferraro 2009). Our analysis shares similarities with these two existing studies, but instead of using a reverse auction to elicit willingness to accept public-goods provision, we use an experimental auction to elicit willingness to pay (WTP) for purchase of a private good with public benefits—LLL. In addition to capturing farmer WTP for the technology, the auction serves as the gateway to an RCT, where technology recipients who actually pay for and receive LLL services are randomly selected from a pool of farmers who wanted to adopt it at some price. Following Chassang, Padró i Miquel, and Snowberg (2012), this "selective-trial" design allows us to estimate the benefits of the technology for farmers that chose to use it (marginal treatment effect, or MTE) as well as to estimate benefits as a function of WTP.

After presenting a conceptual framework to structure our analysis, we estimate the benefits of using LLL among farmers who wanted to adopt LLL and test how these benefits coincide with farmer WTP. We find that, on average, LLL reduces groundwater pumping and diesel fuel for pumping by 24% and reduces diesel costs by roughly Rs 350 per acre in the first year. We also find that these benefits increase with WTP. We then analyze the relationship between observable variables and farmer WTP for LLL services. We use these initial estimates to devise a more direct and policy-relevant test of segmentation and targeting strategies. Specifically, we leverage our auction data to characterize demand for LLL across different subsets of farmers, including possession of an official "below the poverty line" (BPL) card provided by the government, which is otherwise used as a targeting criterion for the government's social protection programs. On the basis of detailed cost data from our LLL service provider, we then characterize the cost structure of LLL provision. The combined analysis of farmer demand, farmer benefits, and LLL provider costs enable us to test the cost-effectiveness of specific targeting strategies on the basis of several metrics, including LLL expansion over acres and households, water savings, and consumer surplus. We conclude with a discussion of the implications and contributions of this work.

II. A Conceptual Framework

A producer's WTP for a technology is based on their profitability with and without the technology, assuming that other inputs are optimized, and may consequently vary across these two scenarios. We use a simple conceptual model to capture this idea, along with key features of the LLL technology we study, and to motivate the empirical analyses in subsequent sections. For simplicity, assume that farmers are risk-neutral profit maximizers and must choose to level their plots with traditional techniques or LLL custom-hire services—an unfamiliar technique to remedy a familiar problem.[3] We assume that LLL is scale neutral and requires no fixed costs of the farmer.[4] Farmer i maximizes expected profits for each plot j and for each technology k, where T and L denote traditional leveling and LLL, respectively:

$$\max_{\mathbf{x}_{ij}^{k}} E\pi_{ij}^{k} = E\left[y_{ij}^{k}\left(\mathbf{z}_{i}, \boldsymbol{\varphi}_{ij}^{k'}\mathbf{x}_{ij}^{k}, \mathbf{s}_{ij}\right) - c\left(\mathbf{z}_{i}, \mathbf{x}_{ij}^{k}, \mathbf{s}_{ij}\right)\right], \tag{1}$$

for $k \in \{\mathrm{T}, \mathrm{L}\}$, where $y_{ij}^{k}(\cdot)$ is the value of total annual production, $\mathbf{z}_i$ is a vector of farmer characteristics, $\mathbf{x}_{ij}^{k}$ is a vector of $h = 1, 2, \ldots, H$ inputs (for example, water, labor, fertilizer, chemicals), $\mathbf{s}_{ij}$ is a vector of plot characteristics, and $c(\cdot)$ is a cost function of farmer- and plot-specific variables that converts production inputs in physical units (e.g., water) into their associated input costs in money terms (e.g., cost of diesel for pumping water).[5] The vector $\boldsymbol{\varphi}_{ij}^{k}$ contains an efficiency parameter for each input h that indicates the proportion of the input that

[3] 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).

[4] This is plausible, given that the overwhelming majority of leveling is done by custom hire on small farms in northern India. In our sample, only 3% of farmers have their own traditional leveler.

[5] While input costs might vary, depending on transaction costs, differential irrigation costs present the main motivation for allowing the model to accommodate farmer-specific cost functions. Most farmers (86%) rely primarily on diesel-powered pumps, for which they pay fuel costs. Some farmers, however, use canal irrigation, for which they do not pay out of pocket but may face quantity constraints. In this case, the cost would be a shadow cost rather than an out-of-pocket cost.

goes to crop production, which is a function of plot characteristics $\varphi^k_{ijh} = \varphi^k_{ijh}(\mathbf{s}_{ij})$ and is assumed to be at least partially observable to farmers. For a given vector $\mathbf{s}_{ij}$ and flood-irrigation water ($h = 1$), we assume that the efficiency parameter for a laser-leveled plot is greater than that for a traditionally leveled plot, that is, $0 < \varphi^{\mathrm{T}}_{ij1} < \varphi^{\mathrm{L}}_{ij1} \le 1$, since a portion of the water applied to an unleveled plot is used only to raise the water level to the highest point of the plot rather than to increase crop production directly. For other inputs ($h = 2, \ldots, H$), we assume $0 < \varphi^{\mathrm{T}}_{ijh} > \varphi^{\mathrm{L}}_{ijh} \le 1$.

Once the farmer solves equation (1) for $\mathbf{x}^{k^*}_{ij}$ for all technology choices, the annual expected net benefits of LLL emerge from a simple comparison of expected profits with traditional versus laser leveling, excluding the cost of either:

$$\begin{aligned}\Delta E\pi^*_{ij} = {} & E\left[y^{\mathrm{L}}_{ij}\left(\mathbf{z}_i, \boldsymbol{\varphi}^{\mathrm{L}'}_{ij}\mathbf{x}^{\mathrm{L}^*}_{ij}, \mathbf{s}_{ij}\right) - c\left(\mathbf{z}_i, \mathbf{x}^{\mathrm{L}^*}_{ij}, \mathbf{s}_{ij}\right)\right] \\ & - E\left[y^{\mathrm{T}}_{ij}\left(\mathbf{z}_i, \boldsymbol{\varphi}^{\mathrm{T}'}_{ij}\mathbf{x}^{\mathrm{T}*}_{ij}, \mathbf{s}_{ij}\right) - c\left(\mathbf{z}_i, \mathbf{x}^{\mathrm{T}^*}_{ij}, \mathbf{s}_{ij}\right)\right].\end{aligned} \tag{2}$$

If leveling were an annual production input—as is the case for inputs such as seed and fertilizer in $\mathbf{x}^{k^*}_{ij}$—these net benefits would be the basis for farmers' maximum WTP for LLL. But leveling is actually a durable input: a plot that is precisely leveled this year can provide benefits for several years before needing to be releveled. Since the duration of leveling benefits depends on factors such as soil type, local topography, and cultivation and irrigation practices, it is potentially plot specific, τ_j Thus, the maximum premium farmer i is willing to pay for LLL services on plot j, $\Delta\mathrm{WTP}_{ij}$, hinges on this intertemporal expected profit:[6]

$$\begin{aligned}\Delta\mathrm{WTP}_{ij} &= \sum_{t=1}^{\tau_j}\delta^t_i \Delta E\pi^*_{ijt}, \\ \mathrm{WTP}_{ij} &= C^{\mathrm{T}}_j + \Delta\mathrm{WTP}_{ij},\end{aligned} \tag{3}$$

where δ_i is farmer i's discount factor and C^{T}_j is the cost of traditional leveling.

In our empirical analysis below, we cannot estimate direct farmer-specific LLL benefits and instead estimate the average benefits of LLL on the basis of the realized first-year benefits as $\Delta\bar{\pi}^*_{t=1}$. With assumptions about the param-

[6] To keep this conceptual model simple, we exclude the option of not leveling at all, which is akin to assuming that the farmers in this model have not leveled in recent years and must relevel their plots. For simplicity, we also do not explicitly allow for liquidity constraints. In practice, these may constrain the WTP of some farmers. A straightforward extension of this conceptual model could allow for such liquidity constraints to shape WTP as well.

eters C_j^{T}, τ_j, and δ_i and the time profile of LLL benefits beyond year 1, this provides a useful benchmark for farmers' WTP, which is essential to the emergence of a market for custom-hire LLL services. Our selective-trial research design ensures that the relationships between LLL benefits and demand that are detected in our study have genuine market relevance (Chassang et al. 2012). Specifically, farmers are able to predict better than we can the plot-specific efficiency gains associated with LLL, $\Delta\varphi_{ij1}^{\mathrm{L-T}} = \varphi_{ij1}^{\mathrm{L}} - \varphi_{ij1}^{\mathrm{T}}$, on the basis of their familiarity with their plot characteristics and agronomic practices. Thus, for a given farmer, both WTP_{ij} and $\Delta E\pi_{ijt}^{*}$ will reflect his plot-specific prediction of $\Delta\varphi_{ij1}^{\mathrm{L-T}}$ and result in a self-selected set of farmers hiring in LLL services. By using an incentive-compatible auction as the gateway to our LLL RCT, we ensure that our estimate of $\Delta\bar{\pi}_{t=1}^{*}$ is market-relevant (i.e., externally valid), in the sense that it is based on the average benefits of the set of farmers who would most likely self-select into the LLL custom-hire market if or when it emerges.

A. Determinants of Demand

This conceptual model helps to introduce our empirical demand analysis. Equations (2) and (3) suggest that WTP varies not only by characteristics that determine single-year farmer profits with and without the technology (production and cost functions, plot characteristics that determine input efficiency) but also by farmer characteristics, such as discount rate and liquidity constraints. A reduced-form representation of farmers' WTP as a function of plot and farmer characteristics can be estimated as

$$\mathrm{WTP}_{ij} = f\left(\mathbf{z}_i, \mathbf{s}_{ij}, d_i|\boldsymbol{\beta}\right) + \varepsilon_{ij}, \tag{4}$$

which implicitly assumes that time since last leveling and C_j^{T} are also functions of $\mathbf{z}_i$ and $\mathbf{s}_{ij}$. This familiar determinants-of-demand estimation is a mainstay of analysis of experimental auctions and 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 are associated with farmer's valuation of LLL for a given plot, ceteris paribus.

As Lusk and Shogren (2008) described, quantile regression techniques may provide a richer alternative to the standard conditional-mean regression in equation (4). 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 on the basis of a uniform pricing strategy but might be brought into the market via tiered or targeted pricing strategies. While quantile regression characterizes portions of the 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.

B. Mutatis Mutandis Market Segmentation Strategies

While the conventional determinants-of-demand approach can provide insights into how different farmers might value LLL differently, it is less useful for formulating targeting strategies because it is infeasible to target farmers, ceteris paribus. Instead, targeted strategies—whether so-called smart subsidies from a public entity or targeted promotional discounts given by a private firm—can typically target only one dimension 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., above or below the poverty line). An unconditional "mutatis mutandis" approach ensures that changing the targeted variable triggers associated changes in all other variables and provides a better basis for targeting strategies.[7] For example, if an LLL provider (with public subsidy incentives) were considering a strategy that targets farmers below the poverty line, the provider would have to take into account the fact that several other farmer and plot characteristics are correlated with whether a farmer falls into this poverty category or not. Such farmers are likely to have, for example, smaller plots, smaller total landholdings, less education, or tighter liquidity constraints. Thus, a conditional, ceteris paribus coefficient on a dummy variable for "below the poverty line" in equation (4) potentially misinforms formulation of segmentation and targeting strategies. Instead, the provider needs to know how demand for LLL among farmers below the poverty line differs unconditionally (mutatis mutandis) from LLL demand among other farmers.

To understand unconditional valuation, we use farmers' WTP data to construct an aggregate demand function as follows:

$$Q(p) = \sum_i \sum_j q_{ij} \times I\left(\mathrm{WTP}_{ij} \geq p\right), \tag{5}$$

where p indicates the price of LLL custom-hire services, q_{ij} is the area of plot j held by farmer i, and $I(\mathrm{WTP}_{ij} \geq p)$ is an indicator function that indicates whether farmer i is willing to pay at least p to level plot j.[8] This aggregate demand function characterizes the entire distribution of farmers' WTP for LLL, which is particularly useful for exploring deviations from uniform market prices.

[7] Mutatis mutandis, meaning "all else changing as it will," is the antonym of ceteris paribus.

[8] 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 $H(p) = \Sigma_i I(\Sigma_j I(\mathrm{WTP}_{ij} \geq p) > 0)$.

With a trivial extension, we can construct demand functions for a subset of farmers who share an observable characteristic. This demand function for a defined segment is particularly useful for testing different targeting strategies because it characterizes the full, unconditional distribution of WTP for this subset of farmers. Segment demand curves 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:

$$\mathrm{CS}_M = \int_{p_M}^{\infty} Q_M(p)dp . \tag{6}$$

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, positive externalities associated with reduced groundwater extraction and reduced diesel fuel consumption could be captured by additional social welfare (Bhargava, Lybbert, and Spielman 2015). 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. In Section V, we evaluate various LLL delivery strategies from the perspective of a social planner trying to maximize number of adopters, land under LLL, total water saved, or total pumping cost saved by targeting subsidies to farmers along observable dimensions or by offering a discount for the first hour of LLL service. Since this is framed as a social-planner simulation, we do not maximize service providers' profit, but we do measure and take into account the costs and net returns of these private service providers.

III. Research Context and Data

LLL was introduced in the western IGP in 2001 and had expanded to 200,000 hectares by 2008 across western Uttar Pradesh and the states of Haryana and Punjab. More recent estimates from Jat (2012) suggest that the current leveling capacity from approximately 10,000 LLL units in operation across India exceeds 1 million hectares. In Punjab alone, there are an estimated 2,000 LLL units owned by farmers' cooperatives and individual farmers (Larson, Sekhri, and Sidhu 2013), although Jat (2012) suggests that the number may be as high as 5,000. Surveys conducted in this region suggest that farmers seem to perceive substantial benefits associated with LLL but also face a variety of familiar adoption constraints, including the cost of hiring in LLL services (Larson et al. 2013).

Although the western IGP is richer and more agriculturally developed than our study site in EUP, LLL trial results from the region are nonetheless promising. These trials have found large and statistically significant irrigation savings on the order of 10%–30% and some weaker (and statistically less robust) evidence of secondary benefits including increased cultivated area, yield, and net returns (Jat et al. 2006, 2009). Depending on the soil type and on cultivation and harvesting practices, a precisely leveled plot can reap these benefits for several years before needing to be releveled. These and other potential dimensions of heterogeneity in LLL adoption and impact are more pronounced in our EUP study area than in the western IGP, where the market for LLL services is now quite developed.

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, and EUP is the poorest region of the state. During the summer *kharif* growing season, when rice is grown, the southwest monsoons can provide much of the water farmers need, whereas the wheat crop in the dry *rabi* season relies primarily on water pumped from groundwater reserves or nearby rivers (Alkire and Santos 2010). While groundwater provides the foundation for this production system and total groundwater extraction has increased in recent decades, access to rainfall and rivers has forestalled the groundwater crisis now present in other states in northern India.[9]

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 from a population of villages that met specific criteria: (1) the villages shared a similar rice-wheat cropping system and were not consistently prone to flooding that would inhibit rice cultivation, (2) the population in each village was not less than 48 households but not larger than 400 households, and (3) the village was not within a 10-kilometer radius of any other research or extension activities operating in the area that involved LLL or other resource-conserving technologies.[10] With respect to this last criterion, only 1.5% of sample farmers reported ever having heard of LLL. Within each village we

[9] Relatively plentiful groundwater reserves in the region ensure that most farmers can tap the water table with pipes and basic diesel pumps. In other regions, deeper water tables require much greater investment to access, a feature exploited in the empirical work of Sekhri (2011, 2014).

[10] To motivate a separate arm of this study that aims to measure intra- and intervillage social-network effects, the random selection of villages was actually conducted as follows. In each district, four randomly selected villages were initially chosen in accordance with the criteria set forth above. Once these were selected, a "paired" village for each was randomly selected from villages located at a 5-kilometer radius from each initial village. This other study is also the rationale for limiting village size.

randomly selected 20–24 farmers from a village census, including only farmers cultivating plots of at least 0.2 acres, the minimum plot size on which LLL can be conducted. Our initial sample consisted of 478 farmers; all but 15 of these farmers remained in our panel over the 14 months of data collection activities (April 2011–June 2012) described below. These farmers had cultivated a total of 926 plots.

In each village between April and May 2011 (just before the wheat harvest), we first convened an information session with the sample farmers to discuss the mechanics of LLL and its potential benefits and drawbacks. The information session consisted of a short informational video on LLL, distribution of a picture brochure, and a question-and-answer session with a nonsample farmer who had previously received LLL services as part of an extension demonstration.[11] In these sessions, we strove to provide complete and objective information, without promoting the technology, and to be highly consistent across villages. We informed farmers that LLL prices in other parts of India had varied between Rs 400 (Indian rupees) and Rs 800 per hour in recent years but did not reveal any specific price points within this range.[12] We also informed farmers they would have an opportunity to bid on LLL and that the bid options would range from Rs 250 to Rs 800 per hour. This price range was printed on the picture brochure that the farmers could bring home with them for reference. As our second step, we conducted a baseline survey to collect information on the economic activities, demographics, and assets of the selected farmers' households, as well as key information about all the plots cultivated or owned by each farmer.

Two to three days after the information session, we held a binding experimental auction in each village to elicit the WTP for LLL, the full protocol for which is reported in appendix A (apps. A and B are available online). In each auction, each farmer was assigned an enumerator to privately guide him or her through the auction process and record the farmer's 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 to have leveled.[13] For each, the farmer estimated how long it would take to laser level the plot, using as a benchmark the amount of time he or she thought it would take to traditionally level the plot. Enumerators used these estimates to help farmers evaluate the total

[11] The nonsample farmer was the same for all information sessions.

[12] During this period, the average exchange rate was Rs 55 per US dollar.

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

cost of leveling at different prices per hour; these estimates had the additional advantage of underscoring fundamental similarities between LLL and traditional leveling. Then, plot by plot, the enumerator recorded whether or not the farmer was willing to pay for leveling at 10 different prices between Rs 250 and Rs 800 per hour. Once the entire price card was completed, and in the spirit of a Becker-DeGroot-Marschak (1964) mechanism, we revealed the preselected binding LLL price (Rs 350, 300, or 250 per hour).[14] Because there is some evidence that "take it or leave it" offers elicit individual valuation more accurately than the standard Becker-DeGroot-Marschak mechanisms, we discretize this mechanism to convert it to a series of discrete decisions to hire LLL or not at different prices (see app. A; Berry, Fischer, and Guiteras 2015). After two rounds of practice auctions using traditional Indian sweets to familiarize farmers with the auction process, we held one practice LLL auction before conducting the real and binding auction. At the conclusion, enumerators described more than 80% of farmers as having understood the experiment very well or fairly well.[15]

Before concluding the auction session, we divided farmers who bid at or above the preselected price into two groups: one who would get the technology and one who would not (and would not pay for it). 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 deciding who would receive LLL services from among all those qualifying in the auction.[16] Construction of these treatment and control groups enabled us to evaluate the impact of LLL on input usage among farmers who wanted to adopt the technology at some positive cost.

Next, for those farmers who won the lottery to receive LLL services, we coordinated the leveling services to be delivered by four LLL units and associated

[14] 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. In the practice LLL auction, we used Rs 550 in all sessions, which eliminates potential session-specific "game effects" from altering valuation in the binding auction. This is particularly useful for unconditional demand differences, as it reduces variation in WTP that is attributable to the mechanics of the experimental auction. Note that from the farmers' perspective, having a preselected price enclosed in an envelope is indistinguishable from a random price that is drawn in real time. We introduced this price-revelation mechanism in practice rounds and described it openly.

[15] Enumerators were asked to categorize farmers as having understood the auction "very well," "fairly well," or "poorly"; 42% were thought to understand it very well, 38% fairly well, and 20% poorly. In 2012, these rose to 76%, 23%, and 1%, respectively.

[16] At the onset of the project, we were concerned that we would not have the capacity to provide LLL to all farmers who wanted it at the discounted price. This proved to be true, as our entire LLL capacity was used to service those who won the lottery.

operating teams contracted through a single service provider. A member of our research team accompanied these providers as they leveled the plots to ensure compliance with the auction and lottery outcomes and to collect additional data on the leveling time and nonleveling time (i.e., travel/transportation and setup time) required for each plot. We also compiled data on the service provider's capital costs, labor costs, maintenance and repair costs, and depreciation. These data on LLL costs enabled us to capture the cost structure of LLL service providers when testing different targeting strategies. We obtained additional information on capital, labor, staff, maintenance, and repair costs and depreciation in order to characterize the cost structure of LLL providers through consultations with the LLL service providers contracted for this experiment, with other LLL service providers, and with experts involved in LLL research and extension activities in the region.

After the auction and service delivery, we conducted intraseasonal surveys with all study farmers at approximately three-week intervals coinciding with major activity phases of the cropping season, to obtain information with lower recall error on seasonal crop management practices, farm labor allocations, input use, irrigation, and harvest.[17] These detailed, high-frequency surveys allow us to construct measures of water usage based on pump characteristics and pumping duration and frequency. After the subsequent rice and wheat seasons, we administered a second LLL auction 1 year after the first auction, just before the wheat harvest in 2012.[18] Based on bids in this second auction, the aggregate LLL demand curve shifted significantly as a result of familiarity with the technology from 2011 exposure. The upper-left panel in figure 1 depicts these aggregate demand curves by year and denotes statistically significant horizontal demand differences. Kolmogorov-Smirnov (KS) tests indicate that these demand distributions are significantly different overall ($p < .000$).

We use farmers' 2011 and 2012 WTP—before and after initial exposure to LLL, respectively—for different purposes in the analysis below. Farmers' preexposure bids from 2011 provide the gateway to the RCT and the basis

[17] The data used in this study are available via the International Food Policy Research Institute portal on Harvard Dataverse at https://dataverse.harvard.edu/dataverse/IFPRI.

[18] All but 15 farmers in the sample participated in this second auction. Farmers who leveled plots on the basis of their participation in the 2011 auction also participated in the 2012 auction. For each plot that was leveled the previous year, we explained that they should pretend that the plot had not been leveled when bidding on LLL for this already-leveled plot. While these bids were therefore hypothetical, this did not seem to lead to a systematic upward bias in the elicited WTP, as one might expect, a result we attribute to the fact that these same farmers were simultaneously bidding for LLL on plots that had not been leveled, which likely transmitted an aura of incentive compatibility over the entire exercise. We include the auction protocol as appendix A for the script used for these explanations.

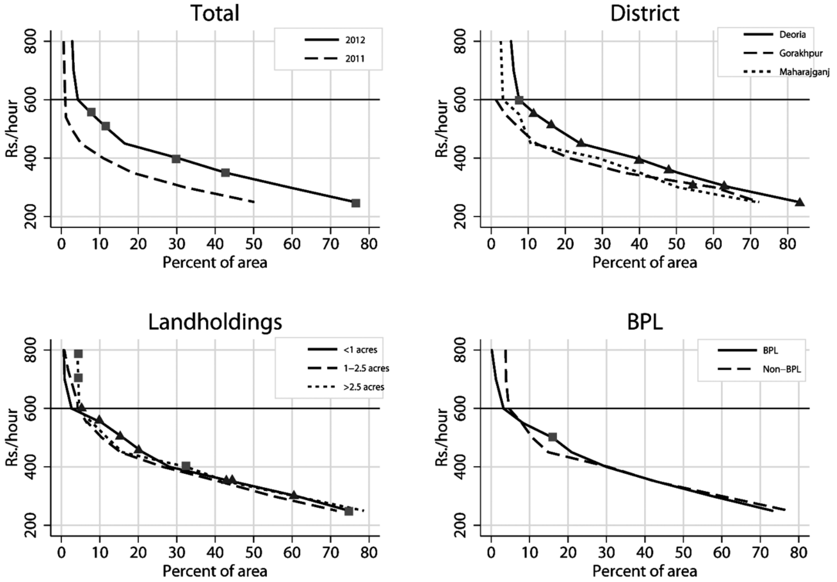

Figure 1. Demand curves for laser land leveling (LLL) derived from willingness to pay in 2012 (except where noted in top left panel) experimental auctions, with market price shown as horizontal line and statistically significant (horizontal) demand differences ($p < .10$) denoted by symbols. Rs/hour = Indian rupees per hour. BPL = below-poverty-line status (whether household head has an official BPL card). The horizontal line at Rs 600 per hour in each panel represents the current market price for LLL custom-hire services. Squares indicate that a given point on a given demand curve is significantly different from another (the other) demand curve at a given price level. When comparing three demand curves (i.e., in the case of landholdings and district), triangles indicate significant differences between a given point and both other demand points at that price level.

of our selective-trial analysis of benefits as a function of farmer WTP. Farmers' postexposure bids from 2012 provide a better indication of initial LLL demand and associated adoption patterns because, by the time of the 2012 auction, most farmers had seen the LLL equipment operate and could more readily compare LLL with very familiar traditional leveling techniques. While they had not yet experienced or witnessed benefits beyond the first year, most should have been able to extrapolate to subsequent years on the basis of their familiarity with traditional leveling and their awareness of the levelness of their plots as clearly evident when irrigating.[19] In sum, when estimating LLL benefits as a function of farmers' WTP, we follow the selective-trial literature and use preexposure bids; when estimating determinants of LLL demand and simulating targeting strategies, we use farmers' postexposure bids as a better approximation of demand in the early stages of diffusion. The evolution of farmers' WTP

[19] Clearly, such rapid learning about the value of a new technology is rare. The same methodology would surely be problematic if applied to other cases of agricultural-technology adoption.

TABLE 1

MEANS FOR SELECTED VARIABLES FOR THE FULL SAMPLE AND FOR TWO SUBSAMPLES FROM THE SECOND ROUND (2012) OF EXPERIMENTAL AUCTIONS ELICITING WILLINGNESS TO PAY

Variable	Full Sample (N = 463) (1)	Out of LLL Market: WTP < Rs 600/hour (N = 443) (2)	In LLL Market: WTP ≥ Rs 600/hour (N = 20) (3)
Age of HH head	50.34	50.36	49.95
	(14.97)	(15.01)	(14.51)
Male HH head	.84	.83	.95
	(.37)	(.37)	(.22)
Education of HH head (years)	6.27	6.27	6.28
	(5.53)	(5.57)	(4.7)
HHs in upper caste	.23	.23	.15
	(.42)	(.42)	(.37)
Wealth index[a]	.50	.50	.48
	(.29)	(.29)	(.29)
BPL cardholder	.47	.47	.45
	(.50)	(.50)	(.51)
Willingness to take risks[b]	4.54	4.53	4.84
	(1.52)	(1.51)	(1.61)
Area owned (acres)	2.96	2.96	3.06
	(7.62)	(7.74)	(4.49)
Plot size (acres)[c]	.67	.66*	.93
	(.98)	(.94)	(1.67)

Note. Standard deviations are in parentheses. LLL = laser land leveling; WTP = willingness to pay; HH = household; BPL = below poverty line.

[a] Factor-analytic index that includes a livestock index, amount spent on Diwali or Eid al Adha, monthly phone bill, condition of house, whether household receives employment through the Mahatma Gandhi National Rural Employment Guarantee Act, domestic and international remittances, whether farmer custom hired a thresher-combine for harvesting, and whether household owns a tractor.

[b] Score ranges from 1 (unwilling) to 7 (willing).

[c] Test of nonzero difference in means between WTP < price and WTP ≥ price; the sample sizes in columns 1, 2, and 3 for this plot-level variable are 1,265, 1,155, and 53, respectively.

* $p < .10$.

after they or those around them experience LLL firsthand provides a unique opportunity to assess the role of social learning in farmer valuation of this technology, which is beyond the scope of this analysis and is the subject of a companion study (Magnan et al. 2015).[20]

Summary statistics on plot and farmer characteristics are given in table 1, first for the whole sample and then for farmers who would be in or out of the LLL market at the then-current price of Rs 600 per hour. If a market for LLL services existed in EUP, a conventional technology-adoption analysis would estimate the correlates of LLL adoption on the basis of this binary, in-or-out-of-the-market comparison. While those in the LLL market are more likely to be male, of a lower caste, and less risk averse, on the basis of a willingness-

[20] A second companion paper provides preliminary analysis of demand heterogeneity using only year-1 data based on an early-stage preview of the project (Lybbert et al. 2013).

to-take-risks elicitation technique proposed and tested by Dohmen et al. (2011), none of these differences is statistically significant—possibly because relatively few of our sampled farmers (less than 5%) valued LLL at or above the current market price.[21] In contrast, even with this small subsample, plots in the market are significantly larger than those out of the market.

Two features of this research design merit brief discussion. First, even though characterizing demand just 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 of the market. For goods or services, such as LLL, that are new to a particular market or otherwise unfamiliar to intended beneficiaries, we believe that experimental auctions, which can elicit valuation as a continuous variable over the full support of the demand curve, can be especially insightful in this regard.

Second, the experimental auction sorts farmers according to their ex ante demand for LLL, and the RCT leverages this (otherwise unobservable) valuation by randomizing access to LLL services by their WTP, thereby allowing us to test for benefit heterogeneity by initial demand. This type of design has recently been elaborated as a selective trial (Chassang et al. 2012), where participants select into an experiment on the basis of how much they value the intervention. One motivation for using selective trials, as opposed to standard RCTs, is that some interventions require (endogenous) effort, and the effectiveness of the intervention is a function of that effort, which is a function of an individual's valuation of the technology. In the case of LLL, very little complementary effort is required to reduce water use. Farmers stop irrigating when water reaches the highest point on the field, which occurs faster—all else equal—for leveled plots. However, because the benefits vary on the basis of other plot features known only to the farmer, benefits likely vary by WTP. Thus, the MTE for farmers with WTP > 0 is likely to be greater than the average treatment effect for all farmers, including those with WTP $= 0$. A selective-trial design in this context enables us to cleanly identify MTEs of those with positive WTP and to estimate benefits as a function of ex ante valuation of the technology even though endogenous effort is not a dominant factor (Chassang et al. 2012). Because these results are specific to farmers most likely to hire LLL services, they can also serve as the basis for simulating the impact of different configurations of subsidies. The price drawn in the auction—the selection criteria in

[21] This elicitation device involves a series of hypothetical questions about farmers' willingness to take risks both in general and when trying new agricultural technologies. To be clear, farmers who express a willingness to take risks are still likely to be risk averse—just less risk averse than those who self-report being less willing to take these same risks.

this selective trial—was intentionally set well below the market price in regions of India where LLL is more established, which improves the external validity of these simulations (i.e., measures of total LLL benefits from a given subsidy are relevant for farmers most likely to be drawn into the market by the subsidy).

IV. Farm-Level Benefits and Demand Heterogeneity

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 by estimating the causal impact of LLL on reductions in input use. We then conduct conventional ceteris paribus analyses of our experimental auction data, namely, regressions of demand determinants. Since targeted delivery strategies must commit to a single targeting dimension, we 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 different segmentation strategies and data from farmers to characterize the water-saving benefits of different segmentation strategies.

A. Farm-Level Benefits

Our primary approach to estimating LLL benefits leverages the lottery mechanism we used in 2011 to determine which farmers actually received and paid for LLL services. This lottery provides exogenous variation among farmers and enables us to test the causal impact of LLL on farm-level outcomes for the subset of farmers who wanted to adopt at a very low price. In this approach, we restrict our analysis to all farmers with at least one "auction-winning" plot ($N = 267$). In some specifications we estimate TOT (treatment-on-the-treated) effects, using the outcome of the lottery as an instrument to predict whether a farmer leveled a plot in 2011, and in others we estimate ITT (intent-to-treat) effects by using the lottery outcome itself as the independent variable. Compliance with lottery outcomes was high, with 85% of lottery-winning farmers receiving LLL and no lottery-losing farmers receiving LLL. Noncompliance was overwhelmingly due to heavy rains that made leveling impossible. Balance tests confirm the validity of the lottery as an instrument: while farmers who qualified for the lottery with at least one "auction-winning" plot are statistically different from other farmers in many ways—which is unsurprising, given the results in table 2—qualifying farmers who won the lottery are statistically indistinguishable from those who lost the lottery (see Magnan et al. 2015). We estimate LLL impacts on several farm-level outcome variables, including groundwater pumping, cost of diesel fuel to pump this groundwater,

TABLE 2
ESTIMATED TREATMENT EFFECTS OF LASER LAND LEVELING (LLL) ON WATER AND DIESEL FUEL USAGE

	Irrigation (log gallons/acre)		Irrigation (000 gallons/acre)		Diesel Cost (Rs/acre)	
	TOT	ITT	TOT	ITT	TOT	ITT
Received LLL	−.242**		−283.1**		−373.6*	
	(.118)		(132.8)		(222.5)	
Won LLL lottery		−.205**		−228.8**		−316.8*
		(.102)		(113.3)		(189.1)
Constant	13.43***	13.43***	1,008***	1,002***	1,815***	1,815***
	(.0720)	(.0730)	(80.75)	(81.40)	(135.6)	(135.9)
Observations	267	267	267	267	267	267
R^2		.015		.136		.010

Note. Standard errors are in parentheses. TOT = treatment-on-the-treated effect; ITT = intent-to-treat effect.
* $p < .1$.
** $p < .05$.
*** $p < .01$.

weeding labor, chemical (pesticide and herbicide) cost, fertilizer use, and yields. We do not use any control variables, as doing so does not substantially alter our point estimates or improve precision, and treatment was randomly assigned.

Because we could feasibly implement the lottery to allocate LLL services only by farmer and not by plot, these impact regressions are conducted at the farm level, using only plots for which the farmer bid at or above the auction price. For WTP, we use the maximum value a farmer bid for any one of their plots.[22] While this reduces our sample size for the RCT, it also increases statistical power by reducing noise. On the basis of the power calculations used to design this RCT, we are confident that the study has sufficient power to detect reasonable first-order LLL effects on water pumping and diesel cost for our full sample. Agronomic trials suggest that possible second-order LLL effects on weeding, chemical use, fertilizer use, and yield are considerably more modest and statistically weaker than the first-order effects on reduced water usage. We are unlikely to have sufficient statistical power to detect these smaller effects.

Overall Treatment Effects

Farmers who received LLL used considerably less water than comparable farmers who did not. Using instrumental variable (IV) estimation to account for noncompliance, we estimate a 24.2% reduction in water use among LLL adopters. This TOT-level effect is equivalent to 283,100 gallons per acre. The ITT effect was slightly smaller, at 20.5%, or 228,800 gallons per acre. The percent reduction in water-use estimates falls at the high end of those found in agronomic trials

[22] Many farmers bid the same amount for all the plots for which they bid a positive amount.

done in India. These reductions in irrigation translate to a decrease in production costs from less pumping. Using IV estimation, we find that LLL adopters spent Rs 374 less per acre on diesel. The ITT effect was Rs 317 per acre. We also tested for potential second-order benefits, including a reduction in weeding labor, reduced chemical (pesticide and herbicide) use, reduced fertilizer use, and increased yield. Our design was not sufficiently powered to detect such results, and indeed we do not find any statistically significant effects.[23] Results for reductions in irrigation and diesel cost can be found in table 2.

These impact results merit further discussion, particularly as they relate to farmers' valuation of LLL, as mentioned in the conceptual model above. In order to compare benefits with farmer WTP, we must calculate savings per hour (as opposed to per acre) of leveling. To do this, we divide Rs 374 by the number of hours per acre it took to level each farmer's land (3 hours per acre, on average), which translates to an average of Rs 158 per hour of direct diesel savings. In practice, LLL benefits persist over multiple years, and, on the basis of field trial found in other studies mentioned above, we assume that these benefits persist over 4 years (i.e., $\tau_j = \tau = 4$). Assuming that these benefits depreciate linearly over time, such that diesel savings in year 5 are 0, our full-sample results translate into total diesel savings of Rs 405 per hour, or Rs 309 per hour with a 20% discount rate. To map these diesel savings into LLL valuation, we must take into account the cost of traditional leveling (C_j^{T})—a standard part of plot preparation in EUP—which ranged from Rs 150 to Rs 250 per hour for hired services. The full-sample results therefore justify an LLL valuation of Rs 500 per hour or more. Including any second-order benefits (e.g., reduced weeding labor) would raise this valuation further. The fact that average WTP for these same farmers is roughly half this implied that valuation might be attributable to binding liquidity constraints or to continued learning about LLL benefits. Either way, targeted strategies may help bridge this gap between implied valuation and demand, particularly once we allow for positive externalities from LLL uptake and diffusion.

Treatment Effects and Demand

Next, we test whether benefits increase with farmer's ex ante WTP. We do this for two reasons. First, if farmers correctly understood the auction and their

[23] Point estimates indicate that weeding time was reduced by 29% for laser-leveled fields (p-value = .154). Perhaps counterintuitively, point estimates for fertilizer and chemical use were positive (6%–10%), indicating that their use was at least as high on laser-leveled fields. These estimates are very imprecise ($p > .4$), so we cannot put much stock in them. However, it is possible that LLL would increase chemical and especially fertilizer use if precisely leveled fields increase their marginal productivity. We find point estimates of 0.049 for wheat yields and −0.099 for rice yields, both of which are very imprecisely estimated ($p > .4$).

bidding incentives, then those who bid the most should have benefited the most. We can test for this relationship to confirm that farmers' bids did reflect their true WTP. Second, because we elicit farmer's ex ante valuation of the technology, we can estimate its benefits as a function of WTP, which will be useful for our policy simulations to follow.

To do this, we regress water and diesel use onto whether or not the farmer won the lottery to receive LLL, WTP per acre, and the interaction of the two.[24] Because of our small sample size, we need to impose this linear structure on the model rather than taking the semiparametric approach of estimating treatment effects over different ranges of WTP. We use WTP per acre, as opposed to WTP per hour, because all benefits are calculated on a per hour basis, and we convert WTP per hour to WTP acre in two different ways. First, we use farmers' own estimates of how long it would take to level their plots (recorded at the time of bidding). Second, we match each non-laser-leveled plot to a similar laser-leveled plot in the same village or its paired village, using the following variables: plot area, whether the plot is upland or lowland, and farmer WTP to level the plot. We then use the time it actually took to level the plots that were laser leveled for their nonleveled counterparts. Mean WTP per acre using farmer-estimated leveling time is Rs 1,519 per acre, and that using matched provider leveling times is Rs 1,308 per acre. The two variables have a correlation coefficient of 0.73% and lead to similar regression results. To ease interpretation, we demean WTP per acre and log WTP per acre before interacting them with treatment status. This way, the coefficient treatment variable is the average benefit, and the coefficient on the interaction term represents the added (decreased) benefit per rupee above (below) average WTP.

From a baseline of approximately 230,000 gallons per acre in water savings, benefits increase by 1,180 (using matched actual leveling times) to 2,370 (using farmer-estimated leveling times) gallons per acre for every Rs 10 increase in WTP per acre. In terms of diesel cost, from a baseline of approximately Rs 300 per acre benefits increase by Rs 2.3 (using farmer-estimated leveling times) to Rs 3.1 (using matched actual leveling times) per acre for every Rs 10 increase in WTP per acre. For both water savings and diesel savings, this amounts to approximately a 0.07%–0.1% increase in benefits for a 0.7% increase in WTP. Results showing heterogeneous benefits by WTP can be found in table 3.

From our regression estimates we can project benefits as a function of WTP. These projections can help us forecast the aggregate LLL benefits generated by

[24] We opt to use ITT effects rather than TOT effects here because of the low correlation between the interaction of winning the lottery and WTP and the interaction of receiving LLL and WTP (0.44 with matched provider leveling time and 0.51 with farmer-estimated leveling time), compared to the correlation between winning the lottery and receiving LLL (0.85).

TABLE 3

ESTIMATED TREATMENT EFFECTS AS MODIFIED BY FARMERS' BASELINE (2011) WILLINGNESS TO PAY (WTP)

	Irrigation Water (log gallons/acre)		Irrigation Water (000 gallons/acre)		Diesel Cost (Rs/acre)	
	Farmer Estimate	Matched Provider Data	Farmer Estimate	Matched Provider Data	Farmer Estimate	Matched Provider Data
Won LLL lottery	−.229**	−.233**	−238.2**	−230.0**	−285.9	−310.1*
	(.0964)	(.0972)	(108.6)	(112.7)	(179.5)	(179.9)
Won LLL lottery × WTP/acre	−.252**	−.175*	−.237***	−.118*	−.233**	−.306***
	(.100)	(.106)	(.0595)	(.0605)	(.0963)	(.0989)
WTP/acre	.356***	.326***	.333***	.228***	.333***	.388***
	(.0647)	(.0661)	(.0438)	(.0386)	(.0613)	(.0730)
Constant	13.45***	13.45***	1,007***	1,003***	1,791***	1,806***
	(.0693)	(.0698)	(78.07)	(80.97)	(129.1)	(130.1)
Observations	267	267	267	267	267	267
R^2	.123	.109	.207	.148	.116	.111

Note. All effects are intent-to-treat effects. Standard errors are in parentheses. "Farmer estimates" refers to WTP per-acre estimates based on farmer projections of time to level land. "Matched provider data" refers to WTP per-acre estimates based on matching leveled to unleveled plots based on observed farmer and plot characteristics (area, owned vs. rented, farmer age, whether plot is upland, WTP per hour). In models with log gallons per acre as the dependent variable (first two columns), WTP is also in logs.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

subsidies with more accuracy than using a single average treatment effect (or a single marginal treatment group for those with WTP > 0). The relationship between effectiveness of a subsidy in achieving maximum benefits and how benefits vary by WTP is nuanced. Generally, and in our case, the benefits of a technology will be increasing in WTP. If those who stand to benefit most have WTP above the market price and those who stand to benefit the least have WTP below the market price, then those incited to adopt by a subsidy will exhibit below-average benefits, and the effect of the subsidy on aggregate benefits will be lower than in the case of homogenous benefits. It is also possible that most (if not all) individuals have WTP below the market price and that only those on the high end of the WTP spectrum will be incited to adopt by a subsidy. In this case, those who exhibit the highest benefits will be incited to adopt by the subsidy, whereas those who exhibit low benefits will not, and the effect of the subsidy will be higher than in the case of heterogeneous benefits. In the simulations we present in Section V, we use projections of water-savings benefits based on WTP to calculate the total water savings of different targeted subsidies.

B. Conditional Demand Determinants and Unconditional Demand Differences

To investigate farm and farmer characteristics that shape demand for LLL, we begin by estimating equation (4), using farmers' updated 2012 bids after their initial exposure to the technology.[25] We first estimate farm-level determinants of demand by regressing the most each farmer is willing to pay for LLL (Rs per hour) at the plot level on farmer and plot characteristics. In addition to these conditional mean functions, we estimate quantile regressions in order to characterize the determinants of farmers' valuation of LLL at points other than mean WTP. Quantile regression techniques are often useful approaches for analyzing auction data because these data rarely follow a normal distribution (Lusk and Shogren 2008). As discussed above, quantile regression also enables us to understand the determinants of demand at different distances from the market price for LLL, which is particularly useful for exploring different targeting strategies. Given this objective, which hinges on farmers' unconditional demand for LLL, we use the unconditional quantile regression estimator proposed by Firpo, Fortin, and Lemieux (2009).[26]

[25] As described in n. 18, farmers who received LLL on a given plot in 2011 were asked in 2012 to bid as if the plot had not been leveled the previous year. Because the overall demand curves including or excluding these previously leveled plots are statistically indistinguishable (in part because these plots represent less than 14% of all plots with positive WTP), we include all 2012 bids in this analysis.

[26] The conventional quantile regression estimator (Koenker and Bassett 1978) generates a conditional quantile function. Thus, a 25th percentile regression estimates a regression line fitted to the 25th per-

For the farm-level characteristics in $\mathbf{z}_i$, we select variables that are commonly associated with technology adoption (see Feder, Just, and Zilberman 1985; Foster and Rosenzweig 2010): age of household head, willingness to take agricultural risks, access to credit,[27] total cultivable land owned, and a factor-analytic wealth index.[28] Because the policy instrument under investigation is meant not to change potentially causal variables as a way of increasing adoption but rather to develop strategies that use observable farm and farmer characteristics to segment the market for subsidization strategies, we are not immediately as concerned with causality as with association. For the plot-level characteristics in $\mathbf{s}_{ij}$, we include variables likely to affect the input efficiency parameters in the vector $\boldsymbol{\varphi}_{ij}^k$ and the overall productivity of the plot. These variables include plot area, whether the plot is upland (not flood prone) or lowland (flood prone), soil type, and the intensity of water use (thousands of gallons pumped per acre) in the season preceding the LLL auction. Farmers pay out of pocket to pump groundwater, but the cost function that translates a given level of water usage to monetary costs is a function of these farmer- and plot-specific variables. Because LLL offers benefits for several years after leveling, we include plot ownership in our regressions, since it likely shapes farmers' willingness to make multiyear investments.[29] Finally, we control for farmers' understanding of the LLL auction.

The ordinary least squares results for the farmer-level specification in table 4 suggest that wealth, baseline water-use intensity, upland plots, and plot size are

centile of the error term (i.e., after conditioning out the effects of all the independent variables). In contrast, an unconditional quantile regression of the 25th-percentile estimates a regression line fitted to the 25th percentile of the dependent variable (i.e., before conditioning). Given that the level of our dependent variable (WTP) in general and the level of this variable relative to a given price level in particular are central to our analysis, this unconditional quantile regression is more useful in principle. In practice, the difference between conditional and unconditional quantile regression results is a function of the fit of the model: the higher the R^2, the greater the difference between the distribution of the dependent variable and the distribution of the error term and, therefore, the greater the difference between the conditional and unconditional quantile estimator.

[27] In the baseline survey, we asked farmers how large an agricultural loan they could get if they wanted to invest in their agricultural operation. They selected from the following loan sizes: Rs 0, Rs 5,000, Rs 20,000, Rs 50,000, and Rs 100,000.

[28] The factor-analytic wealth index employed here consists of total landholdings, thresher hire, combine hire, tractor ownership, large livestock herd size, spending on the Diwali or Eid al-Adha festival, monthly mobile-phone bill, house condition, participation in the Mahatma Gandhi National Rural Employment Guarantee Act public work program, and receipt of migrant remittances.

[29] In these regressions we also include a dummy variable for farmers who understood the LLL auction "very well," according to the enumerator assessment. The WTP for these farmers is higher, but the specification does not necessarily fit their responses better than other farmers. When we exclude the few farmers who understood the auction "poorly," the fit of the model does not change.

TABLE 4

FARMER- AND PLOT-LEVEL DETERMINANTS OF MAXIMUM WILLINGNESS TO PAY (WTP) FOR LASER LAND LEVELING (LLL)

	Max(WTP) by Farmer					
		Unconditional Quantile Regression Percentile				
	OLS	25th (Rs 0)	50th (Rs 250)	75th (Rs 350)	90th (Rs 450)	WTP by Plot Tobit with Farmer Random Effects
Willingness to take risks (1–7 scale)	4.8	4.9	7.0	−.1	−6.8	4.8
	(9.4)	(5.6)	(5.4)	(6.7)	(11)	(8.3)
Largest crop loan available (Rs 000)	.4	.3	.4	.8**	.8	1.0***
	(.3)	(.3)	(.3)	(.4)	(.7)	(.4)
Total land owned (acres)	−4.5***	−4.2***	−3.4**	−3.6**	−1.2	−3.4*
	(1.3)	(1.1)	(1.5)	(1.5)	(2.0)	(1.8)
BPL card = 1	−22	−20	−36**	−24	13	2.3
	(23)	(19)	(18)	(22)	(31)	(25)
Wealth index	22*	18*	13	−.3	51**	−7.1
	(11)	(10)	(13)	(15)	(25)	(17)
Farmer leveled in 2011 = 1	−19	−2.9	−26	3.5	−19	12
	(20)	(17)	(18)	(22)	(34)	(25)
Water use intensity in 2011 (000 gallons/acre)	.03**	.007	.01	.03**	.02	.02*
	(.01)	(.01)	(.01)	(.01)	(.03)	(.01)
Upland plot = 1	41*	54***	11	−5.2	39	25
	(22)	(17)	(20)	(23)	(39)	(22)
Plot size (acres)	25*	16**	16	21	−18	20**
	(14)	(6.8)	(9.9)	(13)	(33)	(8.2)
Constant	199*	199**	283***	448***	447***	117
	(99)	(79)	(77)	(92)	(148)	(99)
Observations	422	422	422	422	422	903
R^2	.209	.165	.177	.170	.136	

Note. Robust standard errors are in parentheses, clustered by village for all farmer-level regressions. Control variables included but not reported: farmer age, plot ownership status, soil type, crop rotation, dummy variable for enumerator assessment that farmer understood the LLL auction "very well," and village fixed effects. For the max(WTP) models, plot-specific variables correspond to the plot with the highest WTP (or the average of the plots in the case that multiple plots received the max(WTP)). OLS = ordinary least squares; BPL = below-poverty-line status (whether household head has an official BPL card).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

all positively associated with WTP.[30] All else equal, total land owned is negatively associated with WTP, which may be due to differences in cropping or farm management practices. The quantile regression results add some additional insights: plot size and upland plot location mainly affect the decision to submit a positive bid for LLL, whereas wealth predominantly affects high bids. Farmers who leveled in 2011 are statistically indistinguishable from other farmers in their demand for LLL, which supports our assumption that learning about LLL is easy, since leveling is a familiar agronomic practice. Given the recent market price range for LLL of Rs 500–600 per hour, the quantile regression results indicate that overall wealth is the only significant determinant of LLL demand among farmers with demand near the market price (i.e., with WTP at the 90th percentile of Rs 450 per hour), but at lower prices other factors become significant as well.

The final column of table 4 contains estimates from a plot-level specification that includes farmer random effects. Because nearly a third of these 903 plots are censored at WTP $= 0$, we estimate this as a Tobit model. These plot-level results are qualitatively similar to the farmer-level results but are more precise, given the larger sample. Specifically, credit, water-use intensity, and plot size emerge as particularly important determinants of LLL demand. These observable factors, along with other plot-specific unobservables, drive farmers' self-selection into the LLL services market by shaping their prediction of $\Delta\varphi_{ij1}^{\mathrm{L-T}}$, which motivates our selective-trial research design.

While these conditional, ceteris paribus comparisons suggest some systematic heterogeneity, the design of the auction also enables us to depict the heterogeneity of LLL demand directly. Figure 1 depicts unconditional, mutatis mutandis demand curves for farmer segments defined by district, total landholdings, and possession of a BPL card. Of the three segmentation dimensions depicted, overall demand differences are most pronounced by district, with LLL demand in the Deoria district higher than that in the other two districts. Given that these are unconditional demand differences, it is important to understand how other variables change when we segment farmers by district. Compared to those of other districts, Deoria district soils tend to be lighter, with less water-holding capacity. Plots in Deoria also tend to be smaller and characterized by upland ecology. Combined, these factors imply that Deoria

[30] Water-use intensity is a function of cropping patterns, local topography, and soil types. Lighter soils such as sandy loam are more susceptible to erosion and undulations caused by continuous tillage and puddling, thus requiring more, or more frequent, leveling, which may be associated with a slightly higher WTP for such services by farmers. Because cropping patterns and soil types are included as control variables (not reported), water-use intensity captures primarily local topography and other more minor factors that influence water usage.

farmers, on average, tend to pump more groundwater than those in other districts, which seems to be an important explanation for these district demand differences; KS tests indicate that the overall demand distribution for Deoria is significantly different from that for the other two districts ($p < .003$), while the distributions for Gorakhpur and Maharajganj are statistically identical ($p = .64$).

Although there are some significant horizontal demand differences by landholdings, KS tests confirm what appears to be true visually and via the simple regressions that generated all the symbols in figure 1: the underlying demand distributions are statistically identical. Disaggregating demand curves according to whether the household head has a BPL card similarly yields demand curves that are nearly indistinguishable from each other. Across all farmer segments, the demand curves in figure 1 are highly inelastic above the market price of Rs 600 per hour but become very elastic below that price, which implies that subsidies could dramatically expand LLL adoption. Less than 10% of the land covered by our sample in any district would be leveled at the market price, but 50% or more would be leveled at half that price. These results allow us to explore ways to cost-effectively increase LLL adoption and decrease water use using targeted subsidies.

V. Policy Extension: Targeting and Segmentation Strategies

In this section, we formulate and evaluate segmentation strategies on the basis of the preceding results and the cost estimates collected from our LLL service providers. The estimated heterogeneity in LLL demand, the detailed cost structure of LLL service providers, and the RCT-based water-saving benefits of LLL provide a platform for this policy-relevant extension of our analysis reported above. Specifically, we simulate possible ways to facilitate the diffusion of LLL in order to leverage positive externalities in terms of more sustainable groundwater usage or information externalities that raise local awareness of the technology. While estimating the magnitude of this positive externality is both complex and beyond the scope of this paper, we are confident in stating that a 24% reduction in groundwater extraction through widespread LLL diffusion cold have a major impact on groundwater exploitation. Targeting strategies may therefore help to facilitate early-stage LLL diffusion and increase positive groundwater externalities.

A. Service Provider Costs

The dominant pricing strategy for LLL custom-hire service providers is to charge farmers a fixed hourly rate for the 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 because the kinds of strategies we explore aim to bring farmers into LLL who might otherwise be priced out of the market. The service costs associated with serving this different mix of farmers may be quite different from the service costs under simple uniform pricing. Any new business or delivery models must therefore reflect the actual cost structure of LLL custom-hire services. Our estimates of LLL providers' cost are based on these cost structure estimates applied to the specific plot-specific provision data collected at the time the service was provided. Because we recruited our service provider from an area of India with a well-established LLL market, we are confident that these costs reflect an operation that is close to the efficiency frontier.[31]

For the purposes of this analysis, we are most interested in the cost of leveling the plots in our sample. On the basis of this cost per plot, we can compute how different targeting strategies affect the net returns of LLL providers. Because we have complete provider cost data for only the 260 plots that were actually laser leveled in either 2011 or 2012, whereas we have WTP data for nearly 900 plots, we must impute costs for the other plots in our sample. To do this we use the plot-matching approach described in Section IV, and we use these matches to estimate leveling, travel, and setup costs for nonleveled plots.[32]

B. Targeting Objectives and Strategies

The targeting strategies we propose are formulated so as to be comparable in their "external" cost (e.g., in the total amount of subsidy allocated to the strategy) and evaluated on the basis of their cost-effectiveness in reducing groundwater extraction and bringing additional farmers into LLL. Using the cost analysis described above, we 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 targeting strategies that provide different subsidy levels to different types of farmers to encourage LLL diffusion. We use

[31] In 2012, an LLL unit cost approximately Rs 350,000. Running a laser land leveler also requires a tractor, which, if the farmers do not already own one, costs Rs 750,000. The service provider is paid Rs 13,000 in wages and other benefits per month, and the supervision cost of operating an LLL unit is about Rs 10,000 for a full season (100 days). Transporting the leveler uses approximately 6 liters of fuel per hour, and operating it on the field uses 5 liters of diesel per hour. The shelf life of a leveler unit is about 10 years, and a tractor has a depreciation rate of 20% per year. The cost of repairing and maintaining a tractor is anywhere between Rs 4,000 and Rs 5,000 after every 100 hours of use, and repairing a leveler unit costs Rs 3,000 after every 300 hours of use.

[32] Using factor analysis, we assigned a score to each plot in our sample based on plot area, whether a plot was upland or lowland, and farmer WTP to level the plot in 2011. Using these scores, we calculated the distance in plot characteristic space between any two plots in the same village pair. Leveling, travel, and setup costs from the nearest leveled plot were imputed for each unleveled plot.

current subsidies on direct purchases of LLL machinery as a benchmark for current public support for LLL and as the total subsidy budget available.

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. Based on the simplifying assumption that the LLL services market is competitive, this equipment subsidy would be transmitted completely to farmers in the form of lower hourly LLL prices. In this case, the most common level of subsidy support for LLL equipment would translate roughly into an effective subsidy of Rs 45–80 per hour in EUP.[33] We take this level of near-term public support for LLL as a benchmark, and we derive and test targeted strategies that are comparable in total public cost to this apparently realistic subsidy level. In what follows, the simplifying assumption of full subsidy transmission to hourly LLL prices makes the comparison between the status quo uniform subsidy and targeted subsidies distinctly conservative. In particular, if LLL service markets are less than perfectly competitive, the subsidy on LLL equipment will be only partially transmitted to lower hourly prices. This implies that the perfect-competition assumption potentially (and conservatively) biases the comparison of a uniform subsidy and targeted strategies in favor of the uniform strategy.

We consider two different targeting objectives. First, if policy makers are primarily concerned about excessive groundwater extraction (and possibly the diesel fuel used to pump this groundwater), then 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 and for farmers who could greatly reduce irrigation by having precisely leveled plots. We consider two metrics to capture this objective: total land leveled and estimated water savings due to LLL, which is directly proportional to reduced diesel fuel use. Second, if policymakers are 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

[33] At the time this study was conducted, the state governments of Bihar, Odisha (formerly Orissa), and Gujarat were offering a subsidy on the purchase of an LLL unit at the rate of Rs 150,000 per unit under the National Agricultural Development Scheme, with an additional subsidy in Bihar of Rs 100,000 per unit provided by the state government. Uttar Pradesh did not have a subsidy. These subsidy programs vary between states in terms of the duration for which the subsidy is available to prospective LLL unit purchasers, the total resources available for subsidizing the purchase of LLL units, and the number of LLL units that can be subsidized in each district of the state. Irrespective of this variation, the Rs 150,000 per unit subsidy works out to a discount of approximately 50% on the purchase price. Using provider-cost breakdowns generated by extension economists in the region, we figure that the 50% equipment subsidy constitutes 26%–37% of total hourly costs, or Rs 45–80 per hour.

level their plots, which provides an obvious metric for evaluating different targeting strategies.[34]

With these objectives in mind, we formulate and evaluate different targeting strategies that we believe could conceivably be feasible to implement. We define feasibility by three dimensions. First, a feasible targeting strategy must use information that is readily observable as the basis for segmentation. To illustrate this dimension, segmenting on plot size—while potentially interesting—is simply infeasible because plots are often defined somewhat arbitrarily by the levees farmers use for water control. Since plot size is mutable and may be endogenous, targeting based on plot size is not viable. For different reasons, segmenting on wealth is generally infeasible because of difficulties in measuring wealth accurately and easily. Proxies of wealth, such as possession of a BPL card, offer a more feasible segmentation option, but in our case the limited demand differences between those with and those without a BPL card (fig. 1) suggest that this proxy may not differentiate demand effectively. As a last example, targeting plots that most need to be leveled may be conceptually compelling, but such a strategy would be infeasible for both the reasons above: the "need to be leveled" is not immutable and is difficult to measure or verify without real effort. Fortunately, the gains from LLL are likely to increase with this plot characteristic and to be at least partially reaped by the farmer, suggesting that the preexisting need for leveling should be reflected in farmers' WTP.

As the second feasibility dimension, we assume that a targeted subsidy scheme must be progressive (or, at least, must not directly disadvantage smallholders relative to large farmers). This is particularly true given the politics of contemporary India. For example, in practice it may 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. Our general approach, therefore, is to formulate targeting strategies that are progressive and then to evaluate these strategies on the basis of how well they achieve the two targeting objectives described above. As the final dimension, a targeted subsidy scheme that relies on the private sector (e.g., the LLL service providers) can be feasible in the long term (i.e., sustainable) only if it properly considers service provider 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 acknowledge that there are deeper cost dimensions beyond these provider costs that

[34] 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 through farmer networks (see Magnan et al. 2015).

shape the practical viability of different targeting strategies. For example, we do not include direct implementation costs in our simulations. We do, however, recognize that administration and monitoring costs are important in practice and that subtle differences in design and monitoring can create opportunities for cheating and rent-seeking behavior.[35]

Taking these feasibility dimensions into account, we formulate different targeting strategies and simulate their impact on LLL uptake, using our farmer-specific demand curves from the second-round auction in 2012.[36] We begin with a status quo uniform market price strategy that simply applies the LLL business model from the western IGP with the current market price of Rs 600 per hour of leveling time. Next, we simulate a simple uniform subsidy of Rs 80 per hour, which is the high-end estimate and upper bound of the effective hourly subsidy of the LLL equipment that exists in other Indian states, as explained above. These two delivery strategies—a market price and a uniform subsidy—provide a benchmark against which targeted subsidies can be compared. To ensure that these strategies are cost comparable, we compute the total subsidy cost of the uniform Rs 80 per hour subsidy when applied to our sample—roughly Rs 18,000—and ensure that all targeted strategies exhaust this same subsidy budget. Below we describe five such targeting strategies.[37]

1. *Perfectly targeted subsidies*. This strategy, which is analogous to first-degree price discrimination, assumes that subsidies can perfectly target farmers who are priced out of the LLL market at a price of Rs 600 per hour. Farmer i is given a subsidy for leveling his plot j equal to Rs $600 - \mathrm{WTP}_{ij}$. These targeted subsidies are sorted from smallest to largest and funded in this order until the subsidy budget is exhausted. Although unrealistic, this strategy provides a useful standard against which the other imperfect (but feasible) targeting strategies described below may be measured.

[35] This issue indicates the need for exploration on how to measure the welfare outcomes from a targeting strategy—inclusive of implementation and monitoring costs as well as the costs of rent-seeking behavior—and how to compare these welfare outcomes with an untargeted (market or uniform) strategy with its own (presumably lower) implementation and monitoring costs and its own costs of rent-seeking behavior. This is a subject of future research.

[36] As explained above, we believe that farmers converge quickly on their final demand for LLL. We therefore take 2012 demand as the point of departure for this simulation exercise. The third-order price discrimination strategies that we evaluate target observables, which assumes that the relationship between LLL demand and these observables is stable over time.

[37] Additional targeting strategies considered were (1) caste, (2) membership in a cooperative or self-help group, and (3) whether the head of household was female. We excluded targeting on caste because it produces results that are quite similar to those for BPL targeting. We excluded targeting on cooperative members and female-headed households because we had too few in our sample to statistically support a simulation exercise based on these subgroups.

2. *Targeting by district*. For a variety of reasons, targeting subsidies on the basis of geographic segmentation is perhaps the most feasible third-degree price discrimination (i.e., targeting-by-segment) strategy. Districts in India are important units of treatment for a host of programs and interventions, which makes this targeting approach quite familiar in the Indian context. 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. Given the mutatis mutandis demand differences in figure 2, we formulate a strategy that offers a Rs 130 per hour subsidy in two districts and no subsidy in the third.
3. *Targeting by landholdings*. The next third-degree strategy segments farmers by landholdings. Although there do not appear to be pronounced differences in LLL demand by landholding, small significant differences do exist, and distributional objectives might make such a strategy appealing. Our analysis of this strategy highlights the opportunity cost of formulating progressive targeted strategies on this basis. While this would certainly be less feasible as a targeting strategy than district targeting, it is not inconceivable and provides a useful benchmark.
4. *Targeting by poverty status*. The final third-degree strategy segments farmers according to their official poverty status. In India, one option for segmenting markets in this way is to offer vouchers to those with BPL cards, but note that figure 1 suggests few systematic demand differences between those with and those without a BPL card. Since this is of-

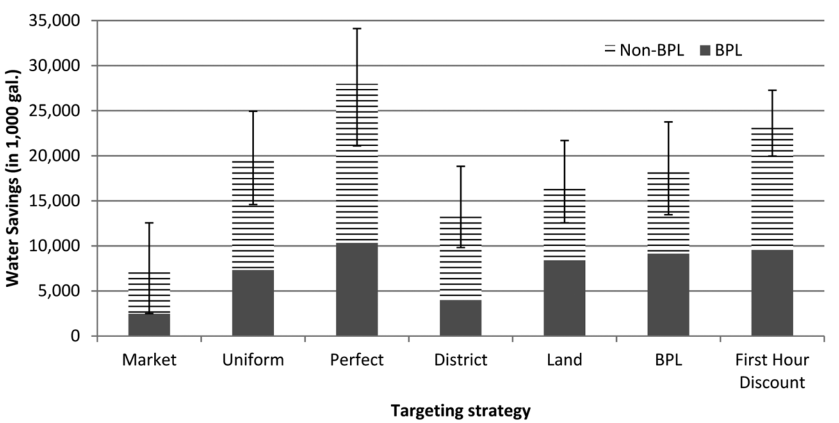

Figure 2. Simulation results by targeting strategy for aggregate water savings by below-poverty-line (BPL) status (whether the household head has an official BPL card), with 90% confidence intervals for total water savings.

ten a popular (and common) segmentation approach in India, simulating such a strategy again highlights the associated opportunity costs.

5. *Implicit targeting by first-hour discount*. The previous three strategies explicitly target defined farmer segments and are therefore analogous to third-degree price discrimination. As mentioned, there is no feasible way to segment by plot size because it is often malleable. To exploit demand differences by plot size, we formulate an implicit targeting strategy that is akin to second-degree price discrimination—a first-hour discount. This parallels a common private-sector marketing strategy and is analogous to the approach used in the neighboring state of Bihar to subsidize the use of mechanical rice transplanting equipment, namely, a subsidy of Rs 1,000 for the first acre transplanted by a given farmer.[38] When each farmer is offered a discount on his first hour of leveling, the effective leveling price becomes farmer and plot specific and varies according to the factors that affect leveling time (e.g., how large and how uneven the plot is).[39] We assume that farmers would make LLL decisions based on this effective farmer-specific leveling price. We apply this effective rate to the farmer's plot with the highest WTP. From the demand for LLL in our sample (and on the assumption that farmers translate the discount into an effective hourly rate), a first-hour discount of Rs 210 exhausts the subsidy budget and generates an effective average leveling rate on applicable plots that ranges from Rs 390–588 per hour, with an average of Rs 444 and a median of Rs 390 per hour.[40]

C. Testing Segmentation Strategies

We evaluate the targeting strategies above using the following metrics: (1) total acreage in the sample under LLL, (2) total number of farmers adopting LLL,

[38] Presumably, this is a limited-time offer that farmers do not expect to receive year after year. We restrict our analysis to one year but assume that any such discount would be offered only for a limited number of seasons or years.

[39] In places where LLL is well established, service providers sometimes offer a lower hourly price or a first-hour discount if more farmers sign up for their services, in order to cover the fixed cost of transportation. If the village is farther than 10 kilometers away, then they will arrange to visit that village and the neighboring areas only if they have a minimum leveling area, even if it implies lowering the hourly rate or offering a first-hour discount.

[40] That this median value equals the lower bound reflects the fact that more than half of all plots have a WTP at or above Rs 390 per hour and that 1 hour or less is required to level that plot. The effective rate described here is for the first candidate plot on each farm, that is, the first plot with the highest WTP. If the per-farmer subsidy is partially used but not exhausted on this plot, a new effective rate emerges for the second plot, and so on until all Rs 210 are used or no more leveling is possible on the farm.

(3) total water savings attributable to LLL, (4) cost-effectiveness of bringing additional acres and farmers into LLL (subsidy cost per additional unit of water saved or farmer), and (5) consumer surplus–based measures of welfare and welfare efficiency. The third and fifth metrics merit a quick explanation.

We use predicted water savings based on farmer WTP for our simulations. By aggregating these water savings over all the plots that are leveled under a given targeting strategy, we estimate total water savings for each strategy. The fifth metric uses a welfare measure to evaluate these targeting strategies. We exploit the farmer-specific demand curves for LLL elicited by the experimental auction for this purpose and compute consumer surplus for a farmer as simply the area between a given price and the farmer's respective demand curve. Using experimental-auction results as the basis for consumer surplus calculations in this way may at first seem cavalier, but this is, after all, precisely how consumer surplus is defined. We use the concept of consumer surplus as a useful construct for capturing and comparing the demand curves elicited in the LLL auction.[41]

Table 5 summarizes the different targeting strategies that we test and includes the percentage of farmers using LLL, acres in our sample that are brought into LLL, and total estimated water savings due to LLL. Relative to the status quo market delivery model, the perfect-targeting and first-hour-discount strategies produce the largest increases by all three of these metrics. Since all the subsidy strategies exhaust the same subsidy budget, these added acres and farmers are directly comparable, suggesting that the perfect-targeting strategy is the most cost-effective approach to expanding acres leveled by LLL and saving water and that the first-hour-discount strategy is most cost-effective for expanding the number of farmers using LLL. We bootstrap this simulation (clustered by household and stratified by district) and depict 90% confidence intervals in figure 2 for water savings. We display the distribution of water savings across BPL cardholders and other farmers as an indication of how progressive the different strategies are in practice.

Although the perfect-targeting and first-hour-discount strategies stand out as the most effective on the basis of this metric and are significantly different from the market outcome, most of the confidence intervals from the six targeting strategies overlap. This would seem to suggest that targeted strategies

[41] We acknowledge that many welfare analysis techniques are more sophisticated than this and do not aim or claim to match this sophistication. The usefulness of consumer surplus as a concept in this case, however, is no different. Instead of estimating demand curves from observational data, our experimental auctions provide directly elicited demand curves that are nevertheless based on reservation prices and therefore have the same economic-surplus interpretation.

TABLE 5

SUMMARY OF TARGETING AND SIMULATION RESULTS

Strategy	Description	Acres Leveled	Farmers Leveling	Water Savings (000 gallons)	Diesel Cost Savings (Rs)	Service Provider: Total Cost (Rs 000)	Service Provider: % Fixed Cost	Service Provider: Revenue (Rs 000)
Market	Rs 600/hour uniform market price	34 (4.2%)	20 (4.2%)	7.13	13,618	30.1	19.6	41.2
Uniform subsidy	Rs 80/hour uniform subsidy on market price	83 (10.3%)	66 (13.7%)	19.55	35,844	91.2	18.8	109.1
Perfect targeting[a]	Farmers with WTP ≥ Rs 600/hour pay market price; farmers with WTP of Rs 475–599 pay their WTP	113 (14.0%)	88 (18.3%)	28.00	51,568	122.5	19.5	150.4
District[b]	Farmers in Deoria pay market price, while farmers in Gorakhpur and Maharajganj pay Rs 470/hour	73 (9.0%)	56 (11.8%)	13.47	27,473	115.7	19.5	93.7
Landholdings[b]	Farmers with >2.5 acres pay market price, those with 1–2.5 acres pay Rs 500/hour, and those with <1 acre pay Rs 475/hour	63 (7.8%)	63 (13.2%)	16.38	30,162	138.2	19.6	84.4
BPL[b]	Farmers with BPL card pay Rs 500/hour; all others pay Rs 544/hour	82 (10.1%)	65 (13.7%)	18.23	33,701	92.0	17.5	125.3
First-hour discount[c]	Rs 210 subsidy on the first hour of leveling by plot	87 (10.7%)	106 (22.2%)	23.51	44,296	101.8	27.6	102.3

Note. Rs = Indian rupees. WTP = willingness to pay. BPL = below poverty line (whether household head has an official BPL card). All targeting strategies exhaust a subsidy budget of Rs 18,000.

[a] Analogous to first-degree price discrimination.

[b] Analogous to third-degree price discrimination.

[c] Analogous to second-degree price discrimination.

are statistically indistinguishable from the status quo uniform subsidy on LLL equipment. Recall, however, that this comparison may be biased in favor of this uniform subsidy. Specifically, any departure from perfect competition in the LLL services market reduces the transmission of equipment subsidies to hourly LLL prices and—without changing the cost of the subsidy—directly diminishes the water savings associated with uniform subsidy. This implies that the water-savings impact depicted for the uniform strategy in figure 2 is an upper bound and that the lower-bound impact (in the case of no price transmission due to market power in the LLL services market) is the market outcome shown in this figure.

Table 5 also includes estimates of total provider costs associated with each strategy. We decompose these costs into fixed costs that do not vary with leveling time (e.g., transportation and setup time, tractor repairs associated with transport between plots) and variable costs that do (e.g., leveling time and tractor and LLL equipment maintenance associated with actual leveling) and display the percentage of total costs that are fixed by this definition.[42] The composition of plots drawn into LLL under the first-hour discount is such that this strategy has the highest share of fixed to total costs, but targeting on landholdings has the highest total provider costs. The revenue reported in this table is based on the hourly rates paid by different farmers in each strategy and does not include the subsidy, which is the same across all scenarios by construction.

To compare the cost-effectiveness of each of these strategies, we compute the subsidy cost per 1,000 gallons of water saved and per farmer leveling and compare these two dimensions of cost-effectiveness in figure 3. In this figure, the total amount of water saved is computed over 4 years, assuming linear depreciation of annual benefits to account for the quasi-durable nature of leveling.[43] The positive correlation between cost per acre leveled and cost per farmer leveling suggests that there are no stark trade-offs between the two metrics and that the six strategies can be rank ordered by cost-effectiveness, with the first-hour discount as the most cost-effective way to save water and perfect targeting as the most cost-effective means of increasing the number of farmers leveling.[44] This figure also depicts the net gain or loss for the service provider, which is computed as profit (based on revenue and cost in table 5) plus the Rs 18,000 subsidy. On the basis of these estimates, service providers would clearly resist the district and landholding strategies. Since perfect targeting is not feasible, the first-hour

[42] We implicitly assume that the provider owns his own equipment (i.e., services no debt) and does not incur overhead in the form of offices or nonleveling employees.

[43] Note that because we observe demand and estimate benefits only in the first year or two, the best we can do to account for the durability of leveling is to make assumptions about the depreciation of water savings over time.

[44] At current exchange rates, the first-hour discount costs less than US$1 per 1,000 m^3 saved.

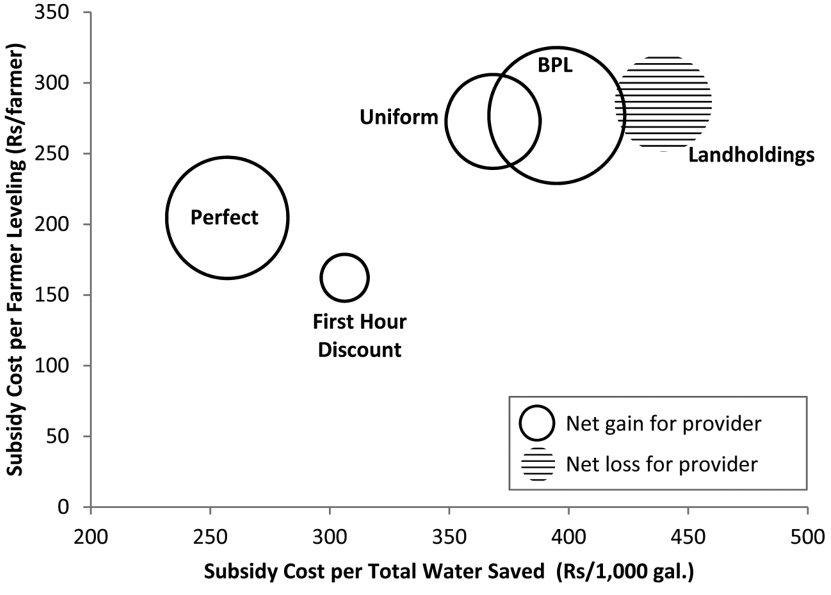

Figure 3. Cost-effectiveness of targeting strategies per water saved and per farmer leveling; bubble size indicates the size of the net gain (loss) to laser land leveling (LLL) service provider. Rs = Indian rupees; BPL = below-poverty-line status (whether household head has an official BPL card). Bubble size indicates profit for private LLL service provider adjusted for Rs 18,000 subsidy.

discount clearly emerges as the most cost-effective viable strategy. The fact that providers offering this first-hour discount just break even when they do not receive the subsidy provides yet stronger evidence that this may be a viable strategy, but keep in mind that these provider costs assume no financing or overhead costs associated with doing business as a service provider. Finally, it is important to clarify that figure 3 depicts static cost-effectiveness—it does not capture anything about the dynamic diffusion path induced by a given targeting strategy.

As a final metric, we estimate consumer surplus by segment as in equation (6), where the segments correspond to the targeting dimension for each strategy. There are limitations to this metric—for example, it accounts for only private benefits associated with LLL, even though public benefits may generate welfare gains as well—but we believe this to be a useful complement to the other metrics, as it is based directly on farmers' perceptions of LLL benefits and demand for LLL rather than on our estimated benefits. As with the estimated acres in LLL, we bootstrap these consumer surplus calculations to generate confidence intervals. Figure 4 shows the results for this welfare metric. The estimated consumer surplus varies widely but often insignificantly across these strategies. The uniform and land-targeting strategies generate the highest consumer surplus—with the first-hour strategy generating slightly more consumer surplus among

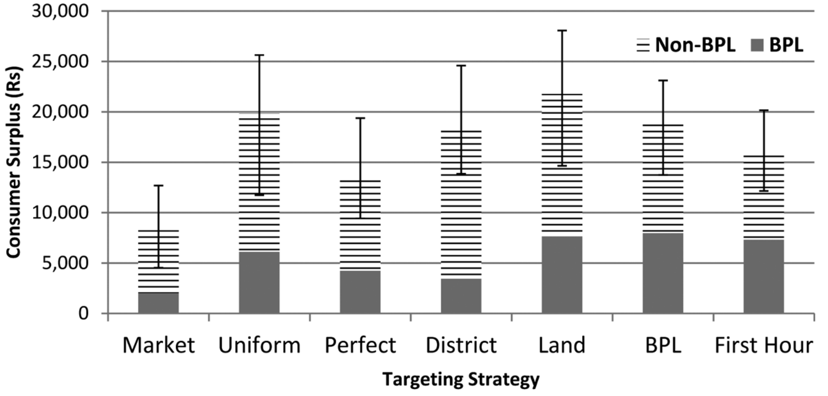

Figure 4. Consumer surplus by targeting strategy and by below-poverty-line (BPL) status (whether the household head has an official BPL card), with 90% confidence intervals for total consumer surplus.

BPL cardholders—followed by the BPL, district, and first-hour strategies. On the basis of the confidence intervals, all but the uniform and perfect-targeting strategies generate more consumer surplus statistically than the market outcome. Once again, however, note that the impact of the uniform strategy depicted in the figure is an upper bound of the true effect and that any departure from perfect competition in the LLL services market would make this impact look more like the market outcome.

Based on the simulation of different targeting strategies described above, the first-hour-discount strategy—an implicit second-degree price discrimination mechanism—seems particularly promising. It performs well relative to other strategies when all of the evaluation metrics are taken into account. Although there may be complexities in implementation, it would also likely be the simplest targeting strategy to implement in practice, with recent precedent in neighboring Bihar. As a preliminary test of this first-hour-discount strategy, we designed and conducted a pilot test in the 24 villages in our sample and 120 randomly selected neighboring villages. This pilot was hampered somewhat by the late onset of the rains in spring 2012 but nonetheless sets the stage for more rigorous market trials. The results of this pilot, described briefly in appendix B, suggest that such a discount may be particularly important as a catalyst for the diffusion of LLL in EUP.

VI. Conclusions

For many agricultural technologies, information asymmetries and incompatible incentives constrain the ability of private agents—rural entrepreneurs, small- and medium-scale enterprises, or large firms—to market technological products and services to small-scale, resource-poor farmers. Often, governments choose broad, unspecific subsidies in the hopes of promoting the rapid diffusion of these technologies. However, such untargeted subsidies are often an inefficient remedy to inherent market failures and a poor use of scarce public resources. One reason why more efficient and more effective alternatives are overlooked is that public policymakers and corporate decision makers lack information about poor farmers' valuation of new agricultural technologies. This vague and incomplete understanding of how different farmers value a technology differently often prevents practical exploration of targeted support mechanisms by both the public and private sectors that can translate into new technological opportunities for smallholders and agricultural-productivity gains and resource conservation for society.

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 an LLL market with a uniform price, we find marked demand differences by district and along other dimensions. Credit constraints, risk aversion, and low perceived benefits seem to explain some farmers' low valuation for LLL.

As a policy extension, we use these results to simulate different targeting strategies aimed at bringing more land under LLL at a lower cost by segmenting markets by observable characteristics, across which technology demand and benefits of use differ. Simulations also show that it is possible to bring more land under LLL at a lower cost by segmenting markets with an implicit second-degree mechanism: a 50% discount on the first hour of leveling. This latter strategy is particularly appealing where policymakers aim to simultaneously provide poor smallholders with access to new technologies while also encouraging market growth and rural enterprise development. A small-scale pilot test of this first-hour discount suggests that it may effectively encourage initial adoption when familiarity with the technology is not widespread.

The experimental methodology and analysis in this paper shed light on targeting considerations and trade-offs associated with promoting agricultural technology among small-scale, resource-poor farmers through public subsidies, private discounts, or some combination thereof. In addition to potential efficiency gains from constructing treatment and control groups on the basis of individual valuation as revealed in an experiment, integrating an RCT into an experimental auction might generate similar insights with other technologies in agriculture, health, nutrition, and energy. In the case of LLL in India, improved targeting strategies based on insights from this analysis are promising because they bring both public and private benefits. Three perspectives on these potential benefits are noteworthy. First, purely private dissemination of LLL services appears to be hampered by a lack of information or uncertainty about market demand among heterogeneous small-scale farmers. Targeted segmentation strategies can incentivize private-sector engagement, bridge that gap between uncertain demand and expected private benefits, and thereby help to reap private benefits that might otherwise be unrealized.

Second, as is often the case with agricultural technologies, there are potentially important externalities associated with LLL that neither farmers nor service providers may take into account. We find that LLL reduces groundwater extraction by 25% on average, with marked heterogeneity in this impact across different targeting dimensions. The diesel fuel savings associated with this reduction confer a clear private leveling benefit, but the reduction also brings public benefits: even small reductions in pumping across a large population can lead water tables to rise, reduce well interference, decrease pumping costs, and improve the sustainable use of groundwater for communities that share groundwater resources (Mukherji 2007; Shah 2007; Bhargava et al. 2015). These potential positive externalities imply that even if the reduced input costs and higher farm profits associated with LLL fade over time as competitive output prices adjust, increased groundwater use efficiency may pay social and environmental dividends long into the future.

Finally, improved targeting strategies can increase returns on public investments in agriculture by enhancing the cost-effectiveness of existing public support for agricultural technologies. In this paper, we take India's existing subsidies for LLL equipment as the baseline for public LLL support and compare targeted strategies on the basis of cost-effectiveness. This analysis suggests that targeted strategies, such as a first-hour discount, are more cost-effective than uniform subsidies, particularly if imperfectly competitive LLL services markets impede the transmission of LLL equipment subsidies to farmers in the form of lower hourly LLL prices. This comparison is inherently static. While a full dynamic evaluation of targeted strategies is beyond the scope of this paper (and likely premature as well), there are potentially important dynamic cost-effectiveness considerations in the case of technology adoption, as recent work on "smart subsidies" in agriculture and health attests (e.g., Ricker-Gilbert et al. 2011; Dupas 2014). To the extent that they initially draw LLL service providers into otherwise underserved markets and incentivize initial adoption among otherwise underserved farmers, targeted strategies can catalyze a diffusion process that can speed the onset of economies of scale, deepen markets for LLL services, and provide substantial gains in dynamic cost-effectiveness over and above the static gains.

References

Aker, Jenny C., Amir Heiman, Bruce McWilliams, and David Zilberman. 2005. "Marketing Institutions, Risk, and Technology Adoption." Unpublished manuscript, Agricultural Issues Center, University of California.

Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A. Olken, and Julia Tobias. 2012. "Targeting the Poor: Evidence from a Field Experiment in Indonesia." *American Economic Review* 102, no. 4:1206–40.

Alfnes, Frode, and Kyrre Rickertsen. 2003. "European Consumers' Willingness to Pay for US Beef in Experimental Auction Markets." *American Journal of Agricultural Economics* 85, no. 2:396–405.

Alkire, Sabina, and Maria Emma Santos. 2010. "Acute Multidimensional Poverty: A New Index for Developing Countries." OPHI Working Paper no. 38, Oxford Poverty and Human Development Initiative, Oxford.

Becker, Gordon M., Morris H. DeGroot, and Jacob Marschak. 1964. "Measuring Utility by a Single-Response Sequential Method." *Behavioral Science* 9:226–32.

Berry, James, Greg Fischer, and Raymond P. Guiteras. 2015. "Eliciting and Utilizing Willingness to Pay: Evidence from Field Trials in Northern Ghana." CEPR Discussion Paper no. DP10703, Centre for Economic Policy Research, London.

Bhargava, Anil K., Travis J. Lybbert, and David J. Spielman. 2015. "Public Benefits of Private Technology Adoption: The Localized Spatial Externalities of Water Conservation in Eastern Uttar Pradesh." IFPRI Discussion Paper no. 1455, International Food Policy Research Institute, Washington, DC.

Chassang, Sylvain, Gerard Padró i Miquel, and Erik Snowberg. 2012. "Selective Trials: A Principal-Agent Approach to Randomized Controlled Experiments." *American Economic Review* 102:1279–1309.

De Groote, Hugo, Simon Chege Kimenju, and Ulrich B. Morawetz. 2011. "Estimating Consumer Willingness to Pay for Food Quality with Experimental Auctions: The Case of Yellow versus Fortified Maize Meal in Kenya." *Agricultural Economics* 42, no. 1:1–16.

Demont, Matty, Pieter Rutsaert, Maïmouna Ndour, Wim Verbeke, Papa A. Seck, and Eric Tollens. 2013. "Experimental Auctions, Collective Induction and Choice Shift: Willingness-to-Pay for Rice Quality in Senegal." *European Review of Agricultural Economics* 40, no. 2:261–86.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner. 2011. "Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences." *Journal of the European Economic Association* 9:522–50.

Dupas, Pascaline. 2014. "Short-Run Subsidies and Long-Run Adoption of New Health Products: Evidence from a Field Experiment." *Econometrica* 82, no. 1:197–228.

Feder, Gershon, Richard E. Just, and David Zilberman. 1985. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development and Cultural Change* 33:255–98.

Feder, Gershon, Anthony Willett, and Willem Zijp. 2001. "Agricultural Extension: Generic Challenges and Some Ingredients for Solutions." In *Knowledge Generation and Technical Change: Institutional Innovation in Agriculture*, ed. Steven Wolf and David Zilberman, 313–53. Boston: Kluwer.

Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux. 2009. "Unconditional Quantile Regressions." *Econometrica* 77, no. 3:953–73.

Foster, Andrew D., and Mark R. Rosenzweig. 2010. "Microeconomics of Technology Adoption." *Annual Review of Economics* 2:395–424.

Hayes, Dermot J., Jason F. Shogren, Seung Youll Shin, and James B. Kliebenstein. 1995. "Valuing Food Safety in Experimental Auction Markets." *American Journal of Agricultural Economics* 77, no. 1:40–53.

Hoffmann, Vivian, Christopher B. Barrett, and David R. Just. 2009. "Do Free Goods Stick to Poor Households? Experimental Evidence on Insecticide-Treated Bednets." *World Development* 37:607–17.

Jack, B. Kelsey. 2013a. "Constraints on the Adoption of Agricultural Technologies in Developing Countries." Literature review, Agricultural Technology Adoption Initiative, Abdul Lateef Jamil Poverty Action Lab, Massachusetts Institute of Technology; and Center for Effective Global Action, University of California.

———. 2013b. "Private Information and the Allocation of Land Use Subsidies in Malawi." *American Economic Journal: Applied Economics* 5, no. 3:113–35.

Jack, B. Kelsey, Beria Leimona, and Paul J. Ferraro. 2009. "A Revealed Preference Approach to Estimating Supply Curves for Ecosystem Services: Use of Auctions to Set Payments for Soil Erosion Control in Indonesia." *Conservation Biology* 23:359–67.

Jat, M. L. 2012. "Laser Land Leveling in India: A Success." Paper presented at the Asian Development Bank's Postharvest Projects Post-production Workgroup of the Irrigated Rice Research Consortium (IRRC) conference "Lessons Learned from Postharvest and Mechanization Projects, and Ways Forward," Manila, Philippines, May 22–24.

Jat, M. L., Parvesh Chandna, Raj Gupta, S. K. Sharma, and M. A. Gill. 2006. *Laser Land Leveling: A Precursor Technology for Resource Conservation*. Rice-Wheat Consortium Technical Bulletin, Series 7. New Delhi: Rice-Wheat Consortium for the Indo-Gangetic Plains.

Jat, M. L., M. K. Gathala, J. K. Ladha, Y. S. Saharawat, A. S. Jat, Vipin Kumar, S. K. Sharma, V. Kumar, and Raj Gupta. 2009. "Evaluation of Precision Land Leveling and Double Zero-Till Systems in the Rice-Wheat Rotation: Water Use, Productivity, Profitability and Soil Physical Properties." *Soil and Tillage Research* 105:112–21.

Koenker, Roger, and Gilbert Bassett Jr. 1978. "Regression Quantiles." *Econometrica* 46, no. 1:33–50.

Larson, N., S. Sekhri, and R. Sidhu. 2013. "Adoption of Laser Levelers and Water-Saving in Agriculture: Report on a Follow-Up Pilot Study." IGC Working Paper, International Growth Center, London.

Lusk, Jayson L., and Jason F. Shogren. 2008. *Experimental Auctions: Methods and Applications in Economic and Marketing Research*. Cambridge: Cambridge University Press.

Lybbert, Travis J., Nicholas Magnan, Anil K. Bhargava, Kajal Gulati, and David J. Spielman. 2013. "Farmers' Heterogeneous Valuation of Laser Land Leveling in Eastern Uttar Pradesh: An Experimental Auction to Inform Segmentation and Subsidy Strategies." *American Journal of Agricultural Economics* 95, no. 2:339–45.

Ma, Xiaochen, Sean Sylvia, Matthew Boswell, and Scott Rozelle. 2013. "Ordeal Mechanisms and Information in the Promotion of Health Goods in Developing

Countries: Evidence from Rural China." REAP Working Paper no. 266, Resource and Energy Analysis Programme, Stockholm Environment Institute.

Magnan, Nicholas, David J. Spielman, Travis J. Lybbert, and Kajal Gulati. 2015. "Leveling with Friends: Social Networks and Indian Farmers' Demand for a Technology with Heterogeneous Benefits." *Journal of Development Economics* 116:223–51.

Masters, William A., and Diakalia Sanogo. 2002. "Welfare Gains from Quality Certification of Infant Foods: Results from a Market Experiment in Mali." *American Journal of Agricultural Economics* 84, no. 4:974–89.

Melton, Bryan E., Wallace E. Huffman, Jason F. Shogren, and John A. Fox. 1996. "Consumer Preferences for Fresh Food Items with Multiple Quality Attributes: Evidence from an Experimental Auction of Pork Chops." *American Journal of Agricultural Economics* 78, no. 4:916–23.

Mukherji, Aditi. 2007. "The Energy-Irrigation Nexus and Its Impact on Groundwater Markets in Eastern Indo-Gangetic Basin: Evidence from West Bengal, India." *Energy Policy* 35:6413–30.

Ricker-Gilbert, Jacob, Thomas S. Jayne, and Ephraim Chirwa. 2011. "Subsidies and Crowding Out: A Double-Hurdle Model of Fertilizer Demand in Malawi." *American Journal of Agricultural Economics* 93, no. 1:26–42.

Sekhri, Sheetal. 2011. "Public Provision and Protection of Natural Resources: Groundwater Irrigation in Rural India." *American Economic Journal: Applied Economics* 3, no. 4:29–55.

———. 2014. "Wells, Water, and Welfare: The Impact of Access to Groundwater on Rural Poverty and Conflict." *American Economic Journal: Applied Economics* 6, no. 3: 76–102.

Shah, Tushaar. 2007. "Crop per Drop of Diesel? Energy Squeeze on India's Smallholder Irrigation." *Economic and Political Weekly* 42, no. 39:4002–9.

Suri, Tavneet. 2011. "Selection and Comparative Advantage in Technology Adoption." *Econometrica* 79, no. 1:159–209.