Diffusing to Level Fields: Evolution of Laser Land Leveling Technology Markets in India

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Abstract

We study the early phase of diffusion of a water-saving, land preparation technology — laser land leveling (LLL) — in the eastern part of Uttar Pradesh, India where the villages had relatively little exposure to the technology prior to 2010. We use a program intervention that allowed random villages in the study area to obtain LLL in 2011 and 2012. Using this random LLL adoption, we examine the role of information in the early diffusion of LLL. Identification of factors contributing to LLL adoption in villages is problematic due to simultaneity between LLL adoption in villages and the emergence of service providers and due to omitted variable bias from unobserved variables influencing LLL demand. The study uses a procedure analogous to the Olley and Pakes (1996) method to identify the parameters related to the influence of service providers in a village's LLL adoption. The research findings show the program intervention is not critically associated with the diffusion of LLL in the study region. Moreover, private-sector service providers are a critical source of LLL diffusion.

1 Introduction

The spatial and temporal heterogeneity in agricultural mechanization is linked to differences in agricultural productivity, economic growth, and poverty reduction within and across developing and developed countries (Foster and Rosenzweig, 2010). Since the onset of the Green Revolution in the 1960s, the diffusion of agricultural mechanization provided greater input efficiency by transforming power- and labor-intensive operations and the adoption of high-yielding crop varieties increased the use of other complementary inputs such as fertilizer and irrigation water (Biggs and Justice, 2015). However, the current wave of agricultural transformation contrasts the mechanization experience during the Green Revolution era (Zhang et al., 2017). The recent emergence of private-sector custom-hiring services in many developing countries is changing the landscape of agricultural mechanization by making mechanization profitable for smallholder farmers. Indian agriculture is also experiencing rapid mechanization and the adoption of power-intensive equipment: tractor use increased by about 28 times between 1970 and 2010 and the use of power tillers grew by over 21 percent in the same period (Kienzle et al., 2013). Whereas power use on farms has increased from 0.3 to 1.7 kilowatt per hectare between 1971 and 2011, the share of agricultural workers and draft animals has reduced from 60.5 percent to 13.2 percent in the same period (Mehta, 2013).

The "first wave" of mechanization literature, emerging during the Green Revolution, found evidence of land size, tenure security, credit availability, education, and extension access as being significant determinants of technological adoption during the early phases of the adoption process (Feder and Umali, 1993). Public policy focused on alleviating demand side considerations — by improving information access and providing subsidies to accelerate technology diffusion — with the presumption that the private sector would respond with appropriate supply provisions (Feder and Umali, 1993; Pingali, 2007). Larger landholdings were considered more profitable for the adoption of heavy machineries, and many researchers believed that mechanization would bypass the smallholder farmers in the absence of significant land consolidation reforms (Pingali, 2007; Ruttan, 2002). Whereas mechanization was synonymous with owning equipment during the Green Revolution, the emergence of private-sector custom hire agricultural services in many developing countries is disentangling the adoption and ownership decision, thereby allowing technology services to reach smallholder farmers. Moreover, many small-scale farmers and rural entrepreneurs are experimenting with and selling services with smaller machineries and engines (Biggs and Justice, 2015).

Many developing countries are witnessing this surge in custom hire service provision. For instance, China has been experiencing rapid mechanization since 2004 due to not only increased adoption through ownership but also because of the emergence of specialized outsourced mechanization services (Zhang et al., 2017). These outsourcing services combine the provision of specialized labor and machinery, and enable small landholder farmers to adopt these technologies. Similarly, most Ghanaian farmers hire tractors for land preparation activities from private sector tractor services. To further improve access of machinery to smallholder farmers, the Ghanaian government has subsidized the establishment of private-sector service enterprise centers since 2007, with each center providing services for tractors, trailers, and other small equipment such as plows and harrows (Houssou et al., 2013). In Nigeria, despite the overall low level of tractor-use, more than double the share of farmers rent instead of own tractors, and the private sector accounts for the largest (about 42 percent) share of the tractor custom-hire market (Takeshima et al., 2013).

Indian agriculture is also undergoing rapid mechanization and the emergence of medium and large farmers providing machinery custom-hire services (Keil et al., 2016). Formal custom hiring centers (CHCs) for agricultural machinery were introduced in India in the 1960s, with the highest number of formal and informal CHCs in agriculturally progressive states of Punjab, Haryana, Uttar Pradesh, Uttarakhand, Gujarat, Maharashtra, Karnataka, and Tamil Nadu (FICCI, 2015). Recently, there has also been an upsurge in the number of farmers owning equipment and providing custom-hire services. For example, Keil et al. (2016) find the practice of implementing zero-till wheat using tractor-run zero-till drillers has spread in the state of Bihar primarily through the emergence of service provision: the number of zero-till service providers increased from 17 to 264 between 2010-11 and 2012-13 in the state. However, few studies have examined these recent trends in the diffusion of agricultural technologies through the emergence of service providers in countries such as India and China (Zhang et al., 2017; Keil et al., 2016; Lu et al., 2016; Yang et al., 2013).

The present study examines the diffusion of a water-saving agricultural technology — laser land leveling (LLL) — through the emergence of service providers in the north Indian state of Uttar Pradesh (UP). Laser land leveling allows farmers to reduce irrigation water use by 25 percent, lower irrigation pumping cost by Rs. 350 per acre, and potentially raise farm yields (Lybbert et al., 2017; Jat et al., 2006). Whereas traditional leveling methods, such as a wooden leveler attached to tractors, levels land with $\pm$ 5 centimeter precision, laser land leveling uses a laser transmitter and an adjustable metal drag to level agricultural plots upto $\pm$ 1 cm precision (Jat et al., 2006). The laser leveler is attached to a tractor and generally requires 2 workers to operate the equipment on the field.

Since LLL's first introduction in India in 2001, there has been significant heterogeneity in LLL patterns across the primary agricultural states in the country (Jat, 2012). For instance, farmers and agricultural cooperatives own over 2000 LLL units in Punjab and have leveled approximately one-sixth of the cultivable land in the state (Larson et al., 2016). In contrast, Uttar Pradesh is an interesting case of differential LLL adoption as the western part of the state has witnessed high LLL diffusion as compared to almost no diffusion in eastern UP (EUP) in the early 2000s. In fact, LLL was first introduced and rolled out commercially in western UP.

The heterogenous LLL diffusion in UP is a reflection of low agricultural productivity in eastern UP as compared to the western part of the state – whereas crop productivity in western UP was 2577 kilogram per hectare in 2007-08, it was 1997 kg/ha in EUP (Pandey and Reddy, 2012). Similarly, land productivity was Rs. 51000 per hectare in western UP and only Rs. 30000 in EUP. Eastern UP is also associated with low levels of labor productivity (Rs. 17000/hectare), net irrigated area (75 percent), and landholding size (0.64 hectares). In contrast, labor productivity is Rs. 37000 per hectare, 91 percent area is irrigated, and average cultivated land area is 0.92 hectares in western UP.

Despite low adoption initially, LLL uptake has been steadily increasing in EUP since 2010. As part of a program intervention by the Cereal Systems Initiatives for South Asia (CSISA), LLL was introduced in 25 randomly selected villages in three districts in EUP in 2011.

These villages had not been exposed to LLL prior to the intervention, and the technology intervention not only provided information on LLL use but also an opportunity to adopt the technology. The program team brought four LLL units from western UP for providing LLL custom hire services to farmers and left the intervention site when the intervention ended in 2012. These villages were offered LLL services for two consecutive years and received random levels of exposure to the technology. Whereas only two farmers owned LLL in 2010, 20 farmers owned and custom hired LLL services to other farmers in 2015. Moreover, the technology has been adopted in 288 villages across the three districts in 2015.

The present study examines the role of this program intervention in LLL diffusion. Specifically, the program intervention created a random set of adopters who may have potentially spread information about the technology and accelerated the pace of LLL diffusion in the region. Because LLL provision was random, the intervention allows us to identify the effect of exogenous technology adoption by a few villages. While we study the role of other factors such as access to roads and area cultivated in a manner similar to other technology diffusion studies, we especially focus on the role of service providers in the spread of LLL in EUP.

Most previous studies in technology diffusion assume the technology becomes available to everyone once it is made commerical (Feder and Umali, 1993). However, the simultaneous emergence of service providers — in response to perceived LLL demand in EUP — poses a key identification challenge in modeling LLL adoption. We use the Olley and Pakes (1996) procedure to examine the influence of service provider availability in increasing the probability of LLL adoption. The study provides evidence that the random set of LLL adopters did not accelerate the pace of LLL adoption in the study site. As expected, the emergence of service providers appears to be the biggest factor contributing to the increased probability of LLL adoption across villages. The evolution pattern of LLL in EUP contrasts the trajectory of diffusion in western UP, suggesting low LLL adoption in EUP was not likely due to lack of information, but perhaps due to low LLL demand in the region.

The contributions we make are twofold. Our first contribution is methodological: we apply an approach developed for structural identification of production functions and use it to identify the role of supply shifts in LLL demand. The application is especially relevant when instruments, like exogenous market prices, are not readily available to identify demand systems, as is the case in our study. Second, the research analyzes the role of information in the diffusion of agricultural technologies through the lens of a random initial exposure to the technology. It elucidates the mechanisms through which market failures, such as the lack of information about smallholder farmers' needs, may prevent the private sector from entering new markets. Although we do not find supporting information for the lack of information about LLL demand, the steady rise in LLL custom-hire services in response to the market information appears to be critical in LLL diffusion in EUP.

2 Research Setting and Data

This section describes the initial LLL program intervention and the spatial and temporal evolution of LLL in EUP since 2010. The research team implemented the data collection activities in 2015 to map the LLL diffusion pattern for the six years of LLL adoption. Although EUP comprises 20 districts in UP, we focus on LLL diffusion in only three districts — Maharajganj, Gorakhpur, and Deoria — because the initial LLL program intervention was confined to this geographical area. We also have data from two other neighboring districts, namely Basti and Sant Kabirnagar, but the core of our analysis is based on data from the program intervention districts.

2.1 Initial LLL Program Intervention

In 2011-2012, a research intervention provided LLL custom hire services in 24 randomly selected villages in Maharajganj, Gorakhpur, and Deoria districts as part of the Cereal Systems Initiative in South Asia project, which aims to improve access to resource-conserving technologies in the cereal-growing belt of north India (see Lybbert et al. (2017) and Magnan et al. (2015) for more details). The intervention had chosen four village pairs in each district, with each village pair selected within a 5 kilometers radius of each other and with no prior exposure to LLL. In fact, other villages within a 20 kilometer radius of the selected treatment villages had also not been exposed to LLL before. Before the program intervention, LLL had been introduced in 10 (non-random) villages in EUP in 2010 due to other complementary efforts by CSISA.

In 2011, information about LLL was provided to randomly-selected farmers in the 24 villages (referred to as program villages in the remainder of the paper), and LLL custom hire services were offered at a pre-determined per hour rental price during the 2011 *kharif* (rice) land preparation season. In collaboration with an LLL machine manufacturer, the research team had brought four LLL units and leveled a total of 218.6 acres in custom hire services in the program villages in 2011 (see Table 1). Similar to the first year's intervention, LLL was again offered in the program villages in 2012 and another 128.1 acres were leveled in the program villages.[1] In addition to the sample farmers, the second year intervention also provided leveling services to other farmers in the program villages and to another set of

[1]Benefits from LLL adoption can last for upto 4 years. Since the sample remained the same in both the intervention years, the plots leveled in the first year were not leveled in 2012, and therefore, the total area leveled in 2012 was less than the area covered in 2011.

randomly-selected villages within a 20 kilometer radius of the original program villages. A total of 30.8 extra acres were leveled in the 24 original sample villages and in one other out-of-sample village. By the end of the two program intervention years, 245 farmers had adopted the technology in 25 villages. Deoria had received the highest proportion of LLL services amongst the three districts (50.4 percent), with Maharajganj and Gorakhpur receiving 30.0 and 19.6 percent, respectively. Figure 1 shows the LLL program villages in 2011 and 2012 and the 2010 CSISA LLL villages.

2.2 Evolution of LLL Service Provision

As a first step in understanding the evolution of LLL markets, the research team mapped the population of LLL service providers (SPs) operating in EUP (see Figure 1 for their location). These service providers had purchased the machine with the purpose of leveling their own farms and providing custom hire services to other farmers. First, we created a service providers' list with the help of CSISA members and LLL dealers selling the machinery in the area. Next, we surveyed these service providers to collect information on their LLL custom-hiring business and the village locations where they had provided LLL services since purchasing the machinery.

As Figure 2 shows, the number of LLL service providers increased from 2 to 20 between 2010 and 2015 in all five districts, and 2 service providers amongst this group had purchased 2 LLL units each. Maharajganj had the highest number of service providers in 2015, followed by Deoria and Gorakhpur. As a result of the rise in service provision, the area under LLL has steadily increased from 228 to 2222 acres (as per service provider reports). Figure 3 shows the rise in LLL area serviced since 2010. Moreover, the number of villages adopting LLL had increased from 10 in 2010 to over 300 villages in 2015 in the five EUP districts (Figure 4). The average distance of all service providers from an adopting village reduced from 65.3 kilometers in 2010 to 58.3 kilometers, and the average distance to the closest service provider from an adopting village reduced from 38.0 to 6.5 kilometers in 2015 (see 2).

These service providers had purchased the machinery for approximately Rs. 350,000 and availed a government subsidy of Rs. 150,000 upon purchase (see Table 3).[2] Depending on the distance travelled, the total per day cost of operating LLL (including diesel cost) in 2015 was approximately Rs. 2533, along with Rs. 774 paid to drivers in wages. An average LLL season typically is 75 days – beginning after wheat harvest in April/May and ending before the onset of rice transplanting in July. Although no prior market existed in LLL service provision, the average custom-hire price has been steadily rising from Rs. 516 per hour to Rs. 811 per hour between 2011 and 2015. Figure 5 indicates the heterogeneity in

[2] The amount of the government subsidy has remained the same since it became available in UP in 2010.

LLL custom hire price across districts: in Gorakhpur, the average price in 2015 was Rs. 925 per hour as compared to the average price of Rs. 767 and 783 per hour in Deoria and Maharajganj, respectively.[3]

2.3 Diffusion of LLL Rental Services

Using the information collected from service providers on LLL-adopting villages, the research team conducted village-level surveys in a sub sample of LLL villages. The village surveys also allowed us to verify the LLL village names received from the SPs and construct a final mapping of LLL villages in EUP, as shown in Figure 1. In 2015, 288 villages had adopted LLL using custom hire services in the three program intervention districts. Whereas the average closest distance between two LLL adopting villages was 15.4 kms in 2010, it had reduced to just 2.2 kms by 2015. We also obtained rural infrastructure, demographic, and agricultural production data on all villages in EUP from the 2011 census databased maintained by the Government of India (GOI, 2011). Moreover, these adopting villages had an average population size of 361.7 households, more than three-fourths had access to a well-built road, and an average of 83.8 percent land was under irrigation in these villages. Over 63 and 61 percent villages cultivated rice and wheat, respectively. Moreover, the distance to the closest program intervention village ranges from 1.1 km to 26.9 kilometers. Table 4 shows these characteristics of the adopting villages. In the remainder of the paper, we examine the factors contributing to the diffusion of LLL in EUP.

3 Estimation

3.1 Model

As described in Section 2, the LLL program intervention in 2011-2012 created a set of LLL adopters in 25 randomly-selected villages in EUP. We are interested in examining the influence of the program intervention on the diffusion of LLL in the study area: we want to estimate if the program intervention raised the probability of LLL adoption in other EUP villages. The program intervention may have allowed farmers in other villages to learn about LLL, thereby potentially increasing the probability of adoption in a given year. We assume the probability of LLL adoption of a village v in year t depends on a set of village-level characteristics, such as access to roads and markets. For instance, low connectivity to a road may prevent taking the LLL equipment to a village, thereby lowering the adoption

[3]One Indian Rupee (Rs.) is roughly equal to 0.016 US Dollars.

probability. We also assume the probability of LLL adoption depends on the stock of service providers and the proximity to them from a village. More service providers increase the probability of LLL in a village. Moreover, as the distance to a service provider's village reduces, the probability of adoption by a village may increase. In this village adoption model, we can test the influence of the program intervention by estimating the following equation.

$$Adopt_{vt} = \beta_0 + x_v'\beta + sp_{vt}'\alpha + prog_v'\gamma + [\Omega_{vt} + \epsilon_{vt}] \tag{1}$$

Here $Adopt_{vt}$ is a binary variable and equals 1 if village v adopts LLL in year t and 0 if the village does not adopt in that year. x_v represents a vector of time-invariant, village-level characteristics that may influence the probability of LLL adoption in a village, such as access to a road and the level of irrigation in a village. sp_{vt} is the stock of service providers and the distance to the closest service provider in year t. $prog_v$ denotes a vector of two program intervention variables: the stock of program villages within a 10 kilometer radius of the village and the distance to the closest program village. Beyond 10 kilometers, it is unlikely that information from a program intervention village would flow to village v.[4] Note the program intervention variables are exogenous due to the random selection of these villages.

There are two terms in Equation 1 that are not directly observable, Ω_{vt} and ϵ_{vt}. Ω_{vt} denotes the unobserved heterogeneity in village-level adoption in year t. Intuitively, Ω_{vt} represents the unobserved village-level heterogeneity influencing LLL demand, such as learning about LLL in each year, and is also potentially influencing the probability of LLL adoption. The index of unknown heterogeneity, Ω_{vt}, is known to the village. ϵ_{vt} denotes any other stochastic shock or measurement error in adoption by a village v in year t. ϵ_{vt} captures factors such as unexpected rainfall during the LLL season that may prevent LLL adoption or any other random event that may not allow the service provider from visiting the village. The stochastic shock, ϵ_{vt}, is random and cannot be anticipated by the village.

We are interested in estimating γ to test the influence of the program intervention villages on LLL diffusion. α is also a parameter of interest to us: we want to examine the role of the service providers' emergence in the diffusion of LLL across villages. However, estimating Equation 1 leads to biased and inconsistent estimates in the presence of omitted variable bias and endogeneity. Omitted variable bias arises due to the presence of unobserved heterogeneity as $E[\Omega_{vt}] \neq 0$. Endogeneity arises from the simultaneous emergence of service providers and adopters. Moreover, it is likely that the stock of and distance to service providers, sp_{vt}, is

[4] Based on data collected from the program intervention villages, Magnan et al. (2015) found evidence that farmers in the intervention villages had no agricultural information networks in villages located 5 kilometers away.

correlated with the unobserved heterogeneity shock, Ω_{vt}, causing endogeneity in estimation. [5]

In order to deal with endogeneity and omitted variable bias in our estimation, we use an analog of the control function, semi-parametric approach developed by Olley and Pakes (1996) (OP) and widely used in many applications for estimating production functions in the presence of endogeneity and selection.[6] Although previous approaches on the diffusion of technologies have modeled diffusion as a logistic model, modified exponentials such the log-normal and Gompertz, or as a Weibull distribution, dealing with endogeneity and omitted variable bias together in these models is a non-trivial exercise and does not allow for obtaining consistent estimates (Genius et al., 2013; Abdulai and Huffman, 2005; Feder and Umali, 1993; Karshenas and Stoneman, 1993). Instead, we use the linear probability model (LPM), similar to the OP procedure, to obtain our estimation coefficients of Equation 1 after controlling for endogeneity and omitted variable bias. Linear probability models only give information about the marginal effects of factors influencing the probability of LLL adoption, without giving any information about the shape parameters of the diffusion process. Despite this limitation, we use LPM to obtain consistent estimates for Equation 1.

Given our set-up in Equation 1, we model the adoption and service provider entry decisions in LLL markets. We assume a village's best guess of its unobserved demand in year t, Ω_{vt}, is its value from last year, $t-1$. Moreover, for a given level of service providers in year t, it is likely that a village's probability of adoption increases as the unobserved demand heterogeneity increases. For example, if the unobserved demand heterogeneity includes LLL learning, then villages that have had greater opportunities to learn about LLL have a higher chance of adoption. Next, we model the decisions made by service providers to enter LLL markets and enter a village v in year t. The service providers decide to enter LLL service provision business based on the previous year's LLL market, that is, they make their decision based on the number of LLL adopters and the number of service providers in $t-1$. We assume service providers are totally naive and do not form any expectations about future demand. This assumption about the service provider's decision to enter LLL markets in year $t-1$ allows us to resolve the simultaneity between the emergence of service providers and the adoption in villages in year t. However, the entry of a service provider in a village v in year t is not resolved by this assumption. The service provider enters a particular village in response to existing LLL demand, that is, we assume that the timing of a service provider's entry in a particular village depends on the unobserved demand heterogeneity surpassing a threshold level of demand.

[5]For example, if unobserved heterogeneity includes unobserved learning, it could also influence the stock of service providers, and the service providers could also influence the unobserved learning.

[6]In order to account for endogeneity between unobserved productivity shock and capital, and selection bias due to exit of low productivity firms, Olley and Pakes (1996) developed a control function approach to identify parameter estimates related to the effect of the firm's capital on the firm's output.

The behavioral set-up of unobserved heterogeneity, and LLL adoption and service provider decisions allows us to make four assumptions to structurally identify Equation 1. First, we assume that unobserved demand heterogeneity, Ω_{vt} follows a first-order exogenous Markov process. This follows from the way a village makes the best guess of the unobserved demand heterogeneity. Second, we assume that the stock of adopters is strictly increasing in unobserved demand heterogeneity for a given stock of service providers. Intuitively, this assumption implies that given the stock of adopters in each period depends on the service providers and the unobserved demand heterogeneity, and given that ad_{vt} and sp_{vt} are observables and Ω_{vt} is the only unobservable, we can invert ad_{vt} to obtain Ω_{vt}. We use this assumption to form an estimate of the unobserved demand heterogeneity. The third assumption is about the timing of a service provider in LLL markets. We assume the stock of service providers in each year depends on the previous year's stock of service providers, sp_{vt-1} and ad_{vt-1}. This assumption allows us to remove the simultaneity in the emergence of service providers and LLL adopting villages. Fourth, in an analogy to Olley and Pakes's (1996) exit decision rule, we assume that service providers enter a village when the unobserved demand heterogeneity is greater than a threshold demand. We explain these assumptions in greater detail below.

3.2 Assumptions

This sections describes the assumptions to identify the model specified in Equation 1.

Assumption 1: Unobserved heterogeneity, Ω_{vt}, follows a first-order exogenous Markov process.

Similar to the OP set-up, we assume unobserved heterogeneity follows a first-order exogenous Markov process, that is:

$$\begin{aligned} E[\Omega_{vt}|\Omega_{vt-1}, \Omega_{vt-2}...\Omega_{v1}] &= E[\Omega_{vt}|\Omega_{vt-1}] \\ \Omega_{vt} &= E[\Omega_{vt}|\Omega_{vt-1}] + \zeta_{vt} \end{aligned} \tag{2}$$

This assumption implies future expectations of unobserved heterogeneity in demand in year t only depends on the previous period's realization of Ω_{vt-1}. Equation 2 represents Ω_{vt} as a sum of its conditional expectation in year $t-1$ and a deviation component, ζ_{vt}, in moving from year $t-1$ to year t. By the properties of the Markov process, the expected value of ζ_{vt} conditional on the realization of the previous period Ω_{vt-1} is zero, and forms one exclusion restriction in the identification of α.

$$E[\zeta_{vt}|\Omega_{vt-1}] = 0 \tag{3}$$

Assumption 2: The stock of adopters (ad_{vt}) is strictly increasing in Ω_{vt} for a given stock of service providers.
We assume the stock of adopters is a function of service providers and the unobserved demand heterogeneity, and the stock of adopters is strictly increasing in Ω_{vt}. This assumption is also directly based on the OP assumptions for unobserved demand heterogeneity. We represent this assumption as follows.

$$ad_{vt} = h_t(\Omega_{vt}, sp_{vt}) \tag{4}$$

We do not include the vector of village-level characteristics and the program-intervention variables in $h_t(\cdot)$ because these variables are time-invariant, and the previous values of Ω_{vt} are not included in the function because of the first-order Markov assumption on Ω_{vt}. Note h_t is an EUP market function and is not village-specific, and we assume that h_t changes over time due to changes in the overall LLL market space but does not vary across villages. For example, any changes in LLL subsidy will be captured by $h_t(\cdot)$.

Because we observe the stock of service providers and adopters and because Ω_{vt} is the only unobservable in Equation 4, the second assumption implies we can invert the function to obtain Ω_{vt}. That is:

$$\Omega_{vt} = h_t^{-1}(ad_{vt}, sp_{vt}) \tag{5}$$

Equation 5 allows us to re-write Equation 1 as follows.

$$Adopt_{vt} = \beta_0 + x_v'\beta + sp_{vt}'\alpha + prog_v'\gamma + h_t^{-1}(ad_{vt}, sp_{vt}) + \epsilon_{vt} \tag{6}$$

Assumption 3: The stock of service providers in year t is decided based on the stock of service providers and the stock of adopters in year $t-1$.
The third assumption pertains to the timing of the service provider's entry in LLL markets. We assume the stock of service providers in year t depends on the stock of (and the distance to) LLL adopting villages, and the stock of (and the distance to) service provider villages in the previous period ($t-1$). This assumption suggests a service provider, providing services in year t, had already made the decision to enter the market in the previous year after observing the previous year's adopters and service providers, and making an assessment about the profitability of entering LLL markets. We represent the service provider's entry decision as follows.

$$sp_{vt} = f(sp_{vt-1}, ad_{vt-1}) \tag{7}$$

Equation 7 shows the stock of service providers in year t is a function of the previous year's stock of service providers (sp_{jt-1}) and adopters (ad_{jt-1}).[7]

Because sp_{vt} was decided in the previous year, the third assumption implies that sp_{vt} is uncorrelated with the deviation (ζ_{vt}) in Ω_{vt} between year $t-1$ and t because $\zeta_{vt} = \Omega_{vt} - E[\Omega_{vt}|\Omega_{vt-1}]$. sp_{vt} belongs to the previous year's information set, and therefore, by the Markov assumption, it is uncorrelated with ζ_{vt}. This orthogonality between sp_{vt} and ζ_{vt} means $E[\zeta_{vt}|sp_{vt}] = 0$ and forms another exclusion restriction to identify α. Moreover, we resolve the simultaneity between the emergence of service providers and the adoption in villages in year t by this assumption.

Assumption 4: A service provider enters a village in year t because the unobserved demand heterogeneity in year t is greater than a threshold demand value.
We only observe LLL demand conditional on a service provider going to a village in a given year t. [8] Assumption 4 implies a service provider j enters village v in year t if the unobserved heterogeneity in LLL demand is greater than a threshold value. Intuitively, this assumption implies that a service provider entered a given village because LLL demand existed in the village already and his entry was in response to the existing demand in the village.

Let d_{jt} represent an indicator variable, which equals 1 when a service provider enters a village in year t and is 0 otherwise.

$$\begin{aligned} d_{jt} &= 1 \quad if\ \Omega_{vt} \geq \Omega_t^*(sp_{vt}) \quad for\ j\epsilon[1,J] \\ &= 0,\ otherwise \end{aligned} \tag{8}$$

Equation 8 implies a service provider j (out of the J service providers) entered a village v in year t, that is $d_{jt} = 1$, because the unobserved heterogeneity in demand for that village was greater than a threshold demand value. The threshold demand value is a market variable and depends on the stock of service providers present in the market each year.

Using Assumption 1, we can re-write Equation 8 as follows.

$$\begin{aligned} d_{jt} = 1 &\quad if\ E[\Omega_{vt}|\Omega_{vt-1}] + \zeta_{vt} \geq \Omega_t^*(sp_{vt}) \quad for\ j\epsilon[1,J] \\ = &\quad if\ \zeta_{vt} \geq \Omega_t^*(sp_{vt}) - E[\Omega_{vt}|\Omega_{vt-1}] \quad for\ j\epsilon[1,J] \end{aligned} \tag{9}$$

Equation 9 allows us to write the probability of a service provider's entry as follows.

[7] This assumption implies we could represent the stock of service providers as a sum of previous year's stock of service providers and new service providers added based on the level of previous year's adopters.

[8] Because we observe demand only when a service provider enters a village, our dataset results in an unbalanced panel.

$$
\begin{aligned}
&Pr\{d_{jt} = 1\} = Pr\{\zeta_{vt} \geq \Omega_t^*(sp_{vt}) - E[\Omega_{vt}|\Omega_{vt-1}]\} \quad for\ j \epsilon [1, J] \\
&Pr\{d_{jt} = 1\} = e(\Omega_t^*(sp_{vt}), \Omega_{vt-1})
\end{aligned}
\tag{10}
$$

Equation 10 shows the probability of a service provider j entering a village v is a function, $e(\cdot)$, depending on the threshold demand value $\Omega_t^*(sp_{vt})$ and Ω_{vt-1}.

Based on the notation above, we define an indicator term d_{vt} for any service provider entering a village in year t as follows.

$$
\begin{aligned}
d_{vt} &= 1 \quad if \sum d_{jt} \geq 1 \quad for\ j\epsilon[1, 20] \\
&= 0,\ otherwise
\end{aligned}
\tag{11}
$$

Similarly, using Equation 10, we can represent the average probability of entry of service providers in a village as $P_{vt} = Pr\{d_{vt} = 1\} = \tilde{e}(\Omega_t^*(sp_{vt}), \Omega_{vt-1})$, where $\tilde{e}$ encompasses the probability of entry of each service provider in a village in year t. Moreover, given the stock of service providers depends on the stock of previous year's service providers and adopters (Assumption 3), we can re-write the probability of entry of a service provider in a village in year t as follows.

$$
P_{vt} = Pr\{d_{vt} = 1\} = \tilde{e}(\Omega_t^*(sp_{vt-1}, ad_{vt-1}), \Omega_{vt-1}) \tag{12}
$$

Note, the endogeneity issue in the estimation of Equation 1 is because the probability of a service provider's entry is related to Ω_{vt} and because the probability of a service provider's entry depends on the stock of service providers (through $\Omega_t^*(sp_{vt})$). However, given the Markov assumption for Ω_{vt} and the assumption that the stock of service providers are determined based on the previous year's stock of adopters and service providers (Assumption 3), Equation 12 implies the the average probability of entry depends on factors that are determined based on $t-1$ variables. Therefore, P_{vt} is uncorrelated with ζ_{vt} – the deviation in previous period Ω_{vt-1} and Ω_{vt}. This condition forms another exclusion restriction for identification.

3.3 Estimation Procedure

Based on these assumptions, we now use the steps analogous to the OP procedure to obtain the estimates for α. Intuitively, the estimation method includes two steps. In the first step, we obtain consistent estimates of all other parameters except α by controlling for the unobserved heterogeneity using Assumption 2. In the second step, we identify α by using the Markov assumption on Ω_{vt} together with Assumption 2 to form a proxy for Ω_{vt} and by forming a proxy for the probability of entry of service providers using Assumptions 3 and 4. Using these two proxies in a control function approach, we obtain a consistent estimate of α. We describe the details of the procedure below.

The first step involves using Equation 5 to re-write Equation 6 as follows.

$$\begin{aligned}
&Adopt_{vt} = x_v'\beta + prog_v'\gamma + [\beta_0 + sp_{vt}'\alpha + h_t^{-1}(ad_{vt}, sp_{vt})] + \epsilon_{vt} \\
&Adopt_{vt} = x_v'\beta + prog_v'\gamma + \phi_t(ad_{vt}, sp_{vt}) + \epsilon_{vt} \\
&s.t. \quad \phi_t = \beta_0 + sp_{vt}'\alpha + h_t^{-1}(ad_{vt}, sp_{vt})
\end{aligned} \tag{13}$$

As a first step, we estimate Equation 13: we regress $Adopt_{vt}$ on the vector of village-level characteristics (x_v), the vector of initial intervention village variables ($prog_v$), and a fourth-order polynomial approximation of ϕ_t using ad_{vt} and sp_{vt}. This step allows us to obtain a consistent estimate of β and γ because we have controlled for the unobserved heterogeneity and because x_v is time-invariant and $prog_v$ is exogenous. However, this step does not identify α.

The second step involves using the exclusion restrictions from the assumptions to identify α and uses the following procedure. We first shift terms in the last equation in 13, and express Ω_{vt} and Ω_{vt-1} as follows.

$$\begin{aligned}
h_t^{-1}(ad_{vt}, sp_{vt}) &= \phi_t - \beta_0 - sp_{vt}'\alpha \\
\Omega_{vt} &= \phi_t - \beta_0 - sp_{vt}'\alpha \\
\Omega_{vt-1} &= \phi_{t-1} - \beta_0 - sp_{vt-1}'\alpha
\end{aligned} \tag{14}$$

Next, we also shift terms in Equation 1 and re-write it as follows.

$$Adopt_{vt} - x_v'\beta - prog_v'\gamma = \beta_0 + sp_{vt}'\alpha + \Omega_{vt} + \epsilon_{vt} \tag{15}$$

If we take the expectations on both sides, we get:

$$\begin{aligned}
E[Adopt_{vt} - x_v'\beta - prog_v'\gamma|\Omega_{vt-1}, d_{vt} = 1] &= E[\beta_0 + sp_{vt}'\alpha + \Omega_{vt} + \epsilon_{vt}|\Omega_{vt-1}, d_{vt} = 1] \\
&= \beta_0 + sp_{vt}'\alpha + E[\Omega_{vt}|\Omega_{vt-1}, d_{vt} = 1] \\
&= \beta_0 + sp_{vt}'\alpha + E[E[\Omega_{vt}|\Omega_{vt-1}] + \zeta_{vt}|\Omega_{vt-1}, d_{vt} = 1] \\
&= \beta_0 + sp_{vt}'\alpha + E[E[\Omega_{vt}|\Omega_{vt-1}|\Omega_{vt-1}, d_{vt} = 1]
\end{aligned} \tag{16}$$

Equation 16 follows because sp_{vt} is determined at $t-1$ based on the third assumption and Ω_{vt-1} is uncorrelated with ϵ_{vt} due to Assumption 1. Based on Equation 16, the second stage of the identification procedure solves endogeneity and omitted variable bias together by controlling for $d_{vt}=1$ (endogeneity since the entry of service provider in a village depends on Ω_{vt}) and Ω_{vt} (omitted variable bias due to unobserved demand heterogeneity).

Based on Equation 16, we substitute terms using Equations 12 and 14 and re-write Equation 1 as:

$$\begin{aligned} Adopt_{vt} - x_v'\beta - prog_v'\gamma &= \beta_0 + sp_{vt}'\alpha + E[\Omega_{vt}|\Omega_{vt-1}, d_{vt}=1] + \zeta_{vt} + \epsilon_{vt} \\ &= \beta_0 + sp_{vt}'\alpha + g(\Omega_{vt-1}, P_{vt}) + \zeta_{vt} + \epsilon_{vt} \\ &= sp_{vt}'\alpha + \tilde{g}(\Omega_{vt-1}, P_{vt}) + \zeta_{vt} + \epsilon_{vt} \\ &= sp_{vt}'\alpha + \tilde{g}(\phi_{t-1} - sp_{vt-1}'\alpha, P_{vt}) + \zeta_{vt} + \epsilon_{vt} \end{aligned} \tag{17}$$

Note, by our exclusion restrictions, $E[\zeta_{vt} + \epsilon_{vt}|\Omega_{vt-1}, P_{vt}] = 0$. In the above equation, $g(\cdot)$ is a function of Ω_{vt-1} and P_{vt} and $\tilde{g}(\cdot)$ accounts for both β_0 values. We do not have β, γ, ϕ_{t-1}, and P_{vt}. However, from the first step, we can obtain $\hat{\beta}$, $\hat{\gamma}$, $\hat{\phi_{t-1}}$. We obtain an estimate of $\hat{P_{vt}}$ as follows. We first estimate the predicted probability for each service provider ($\hat{P_{jt}}$) by fitting a probit model on lagged service provider variables sp_{vt-1}, lagged adopter variables ad_{vt-1} (based on the set-up in Assumption 3), as well as their squares and cross products. Using ($\hat{P_{jt}}$), we estimate the average predicted probability of all service providers entering a district in year t and use the average predicted probability as a proxy for $\hat{P_{vt}}$.[9,10] We approximate $\tilde{g}(\cdot)$ as a fourth-order polynomial in $\hat{\phi_{t-1}} - sp_{vt-1}'\alpha$ and $\hat{P_{vt}}$, and use non-linear least squares to estimate Equation 17 and obtain $\hat{\alpha}$.

4 Estimaton Results

In this section, we present our results on the model estimating the determinants of LLL adoption in the study area. As discussed in Section 3, we follow an approach similar to the OP method to deal with endogeneity and omitted variable bias in the estimation of our LLL

[9] In an ideal scenario, we would have used the predicted probability of the service provider that entered a given village. However, we do not have complete data on all the service providers and on which service provider entered which village. Implicitly, we also assume that service providers do not provider services outside their district. This assumption is reasonable because service providers are also farmers and engage in LLL service as a side business.

[10] This part of the procedure varies from the OP approach because Olley and Pakes (1996) use the probability of the firm exiting and estimate the capital coefficient associated with that same firm. Here, we use the probability of a service provider entering villages in his district in year t and estimate the α related to his entry on the adoption decision by a village.

adoption model. We aim to identify the role of service provider emergence and the initial program intervention in LLL adoption across villages in EUP.

We first estimate LLL adoption using linear probability (LP) and probit models. In each estimation, we use a set of time-invariant village-level characteristics including access to a road, the total cultivated area in a village (measured in hectares), the percentage of land irrigated, the percentage of land not irrigated using canals, lakes, and rivers, and the percentage of agricultural population in a village. Heterogeneity in these characteristics may lead to heterogeneity in the timing of adoption across villages. For instance, villages relying heavily on diesel pumps for irrigation may tend to adopt sooner as compared to villages where farmers do not pay for water-use. In addition to these village-level characteristics, we also include the number of program villages within a 10 kilometer radius of the village and the distance to the closest program village to test the role of information flows on diffusion after the LLL intervention. Villages close to the program village may have an increased likelihood for adopting LLL if they gained any exposure to the technology from the set of initial LLL adopters.

In addition to these time-invariant characteristics, we also use two variables for capturing the availability of service providers in the area: the stock of service providers in each time period and the distance to the closest service provider in each period. However, as discussed in Section 3, the estimates associated with these variables may be endogenous to the unobserved heterogeneity in learning across villages. As a first test of omitted variable bias in our estimation, we use the lagged stock of adopters in each time period and the closest distance to an LLL adopting village in the previous period as a proxy for unobserved heterogeneity in learning. However, we should take these estimates with caution because of the stock of service providers and previous period adopters are likely to be endogenous, as discussed in Assumption 2. Because the lagged stock of LLL adopters and current period service providers are positively correlated and because unobserved heterogeneity is also positively related to the probability of LLL adoption in a village, we expect our service providers to have an upward bias if we do not account for unobserved heterogeneity.

Table 5 shows our estimation results from the linear probability and the probit models. We find access to a road increases the probability of adoption by at least 4.6 percentage points based on the two models and is significant in all the models. The point estimate for percentage area under irrigation is very small and significant, but the sign is negative and unintuitive. Specifically, we would expect the probability of adoption to increase with a percent increase in the irrigated area and a percent increase in the area not under lake or canal irrigation. An one percent increase in the number of cultivators in a village is also associated with a 0.3 percent increase in the probability of LLL adoption, which is expected because technology adoption will be higher in villages where more people are engaged in agriculture.

An increase in the number of program villages within a 10 km proximity to the village raises the probability of LLL adoption of a village. However, the point estimate is not statistically significant in all the specifications. The minimum distance of these villages from the program villages ranges from 1.1 to 29.6 kilometers. The results show the probability of LLL adoption increases with an increase in the distance to a program village. Although the sign is unintuitive, these results are also statistically insignificant.[11]

Next, we consider the role of service provider emergence in LLL adoption. When we add the stock of previous year's adopters and the closest distance to a previous year LLL adopting village, we find the point estimates of the service providers' stock significantly reduces suggesting the presence of omitted variable bias. The point estimates associated with the program intervention variables also reduce because of the positive correlation between unobserved heterogeneity and learning due to the program intervention. An increase in the stock of service providers is associated with an increase in the probability of adoption and is significant in all specifications. Moreover, as the distance to a service provider decreases by a kilometer, the probability of adoption increases. The stock of previous period adopters increase the probability of adoption and a reduction in the distance to previous period adopting villages appears to raise the probability of adoption. The estimates for the service providers and the previous-period adopters suggests the presence of two issues: an upward bias in the estimates associated with service providers and program intervention if we do not account for unobserved heterogeneity in learning; and endogeneity resulting from the relationship between unobserved demand heterogeneity and the stock of service providers.

Given the issues of endogeneity and omitted variable bias, we identify our LLL model using the estimation procedure described in Section 3. However, there are two limitations of our empirical approach. First, we can only use a linear probability model as modeling the procedure in other functional forms is a non-trivial exercise. Second, the procedure only identifies the influence of service providers on the probability of adoption. We cannot identify the role previous year's LLL adopters play in increasing the probability of adoption. Table 5 (column 5) shows the OP estimates and the bootstrapped standard errors of the stock of service providers and the minimum distance to them from a village. An increase in the availability of a service provider increases the probability of adoption by 4.2 percentage points. The point estimates related to the minimum distance from a service provider is lower than the LPM estimate, but higher than the probit model's estimate. A kilometer reduction in distance to the service provider increases the likelihood of adoption by 0.2 percentage points.

[11]We also estimated a first-stage regression using village adoption data for 2012 and 2013, but the results did not change significantly in significance or magnitude.

Overall, our three key findings are as follows. First, identifying the role of service providers is fraught with endogeneity and omitted variable bias. As expected, the entry of service providers is a significant contributor in increasing the likelihood of LLL adoption across villages in EUP. Figure 6 shows that the predicted probability of adoption obtained from the probit specification 3 increases in the stock of service providers. Second, the initial program intervention, as proxied by the minimum distance to the intervention and the number of villages within a 10 kilometer proximity to a village, is not significantly associated with increasing the probability of LLL adoption. Third, access to roads, as a proxy of rural infrastructure, seems to significantly accelerate the diffusion of LLL, both in terms of access to information and the travel costs associated with service provision. The effect in magnitude appears to be as large as the effect of service providers in increasing LLL adoption.

5 Conclusion

The present study highlights the significance of service providers, along with access to roads and infrastructure, in the diffusion of LLL in the study region. Whereas the importance of rural infrastructure in improving agricultural productivity is well-known, understanding the characteristics of service providers and the differences between technology adopters and diffusers is gaining greater attention in agricultural policy work in many developing countries. For instance, the Government of Ghana is establishing technology groups that receive about five tractors at subsidized prices and have the potential of reaching 500 farmers in an agricultural season (Houssou et al., 2013). In Kenya, Chassang et al. (2017) are implementing selective trials to identify farmers having a higher willingness to experiment and share information with others. In India, both the government and the private sector are developing innovative business models, such as providing a suite of technologies to custom hire, in order to expand the reach of these services to smallholder farmers. Our study shows that, on average, a service provider reached 16 villages in 2015 as compared to 5 villages in 2010. This scale has steadily increased from 2010 and 2015, and is further expected to rise as service providers gain greater experience with the technology and service provision. Future research work on service provider traits and models analyzing the scalability and expansion of service providers' businesses will further contribute to expanding the reach of agricultural technologies to smallholder farmers.

The research findings also show the program intervention is not critically associated with the diffusion of LLL in EUP. We find the area under LLL steadily increased from 228 to 2222 acres in this period, and the number of service providers rose 9 times from their 2010 level. The research intervention added another 377.5 acres under LLL in 2011 and 2012. The experience of diffusion in western UP contrasts the diffusion trajectory in EUP where

LLL was introduced in 2002 and bought by only a few farmers in 2003. By 2006, 37 farmers owned LLL and the acreage had reached approximately 10, 000 acres in over 10 districts (Jat et al., 2006). The rate of early diffusion in EUP — given the same duration of exposure — is slower than western UP, suggesting the delay in the introduction of LLL in EUP was perhaps not a coincidence and that the evolution of LLL markets was likely due to low LLL demand. However, with the right policy levers — encouraging the development of service providers and the incentives to create demand for smallholder farmers — the pace of LLL adoption in EUP can be accelerated. Ultimately, the way agricultural technologies diffuse across agricultural zones and the factors accelerating mechanization process are fundamental to future agricultural productivity gains for at least the next decade in India.

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Figure 1: Diffusion of Laser Land Leveling in Eastern U.P.

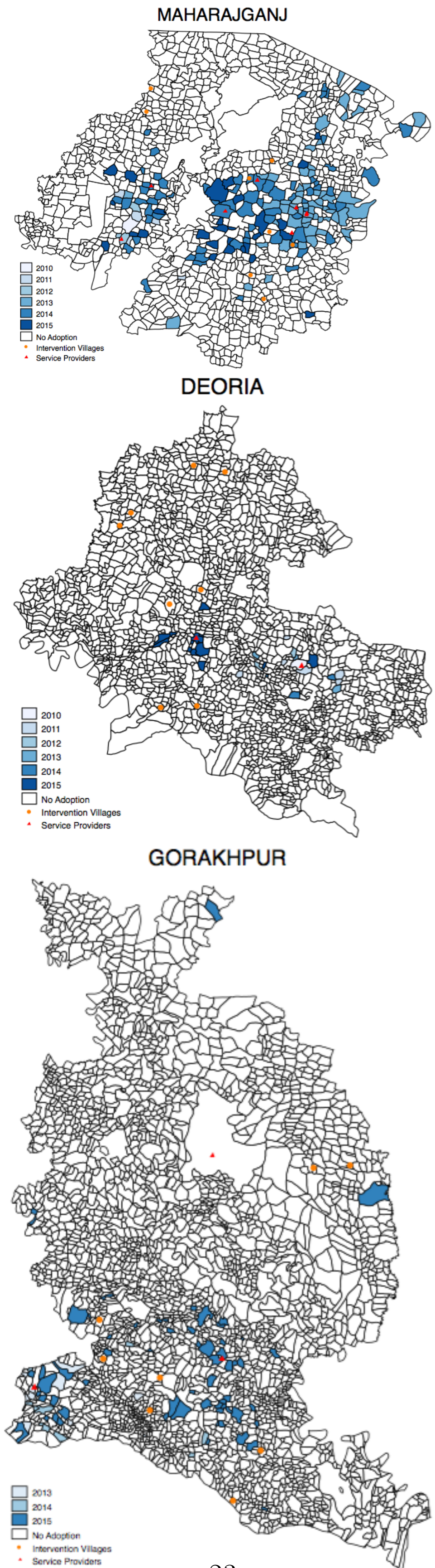

Figure 2: Evolution of LLL Service Providers

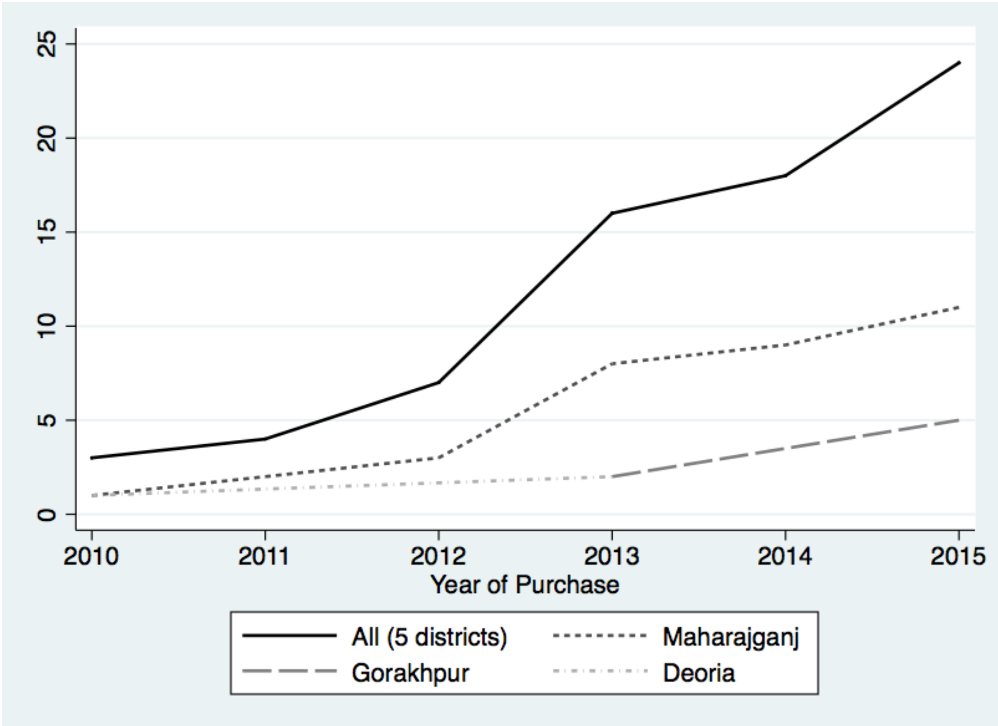

Figure 3: Land Area Under Laser Land Leveling

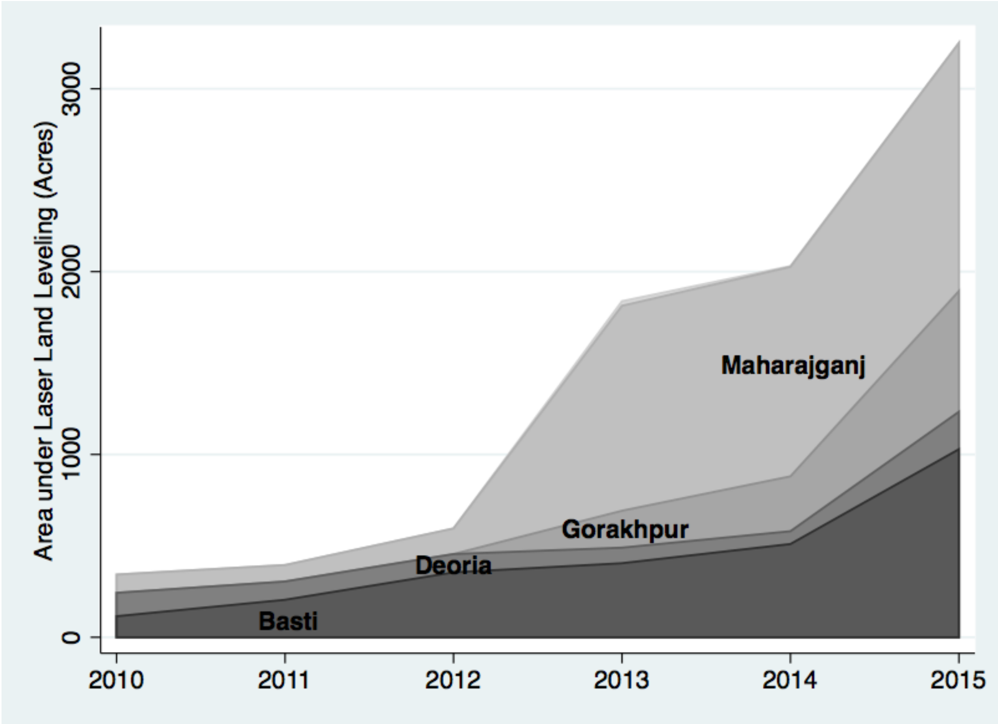

Figure 4: Number of Villages Adopting Laser Land Leveling

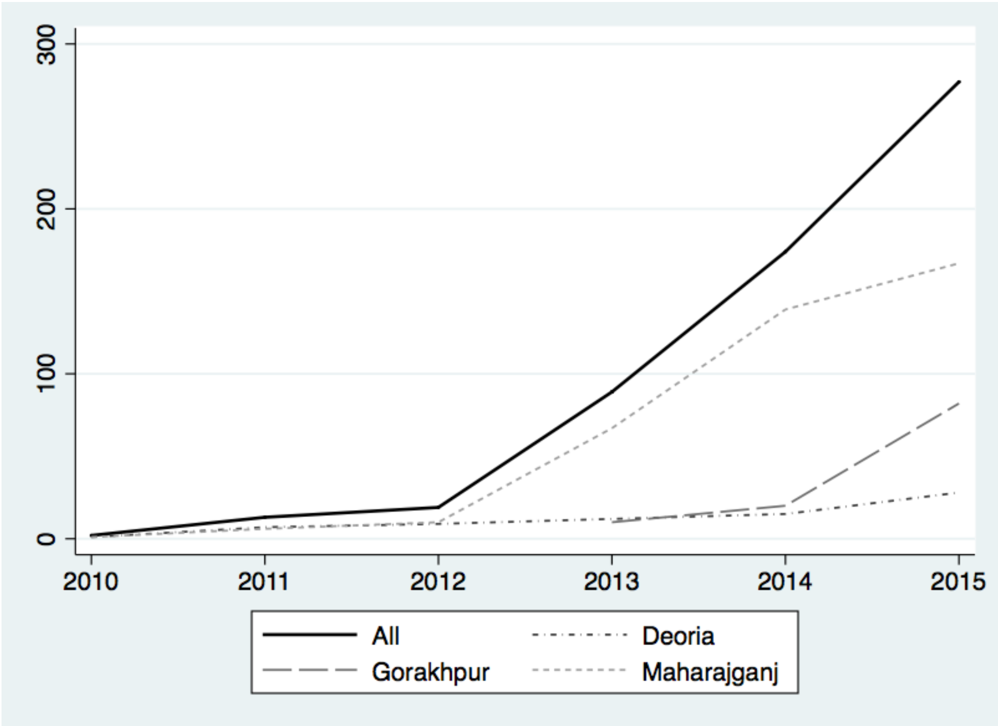

Figure 5: LLL Custom-Hire Prices in Study Districts

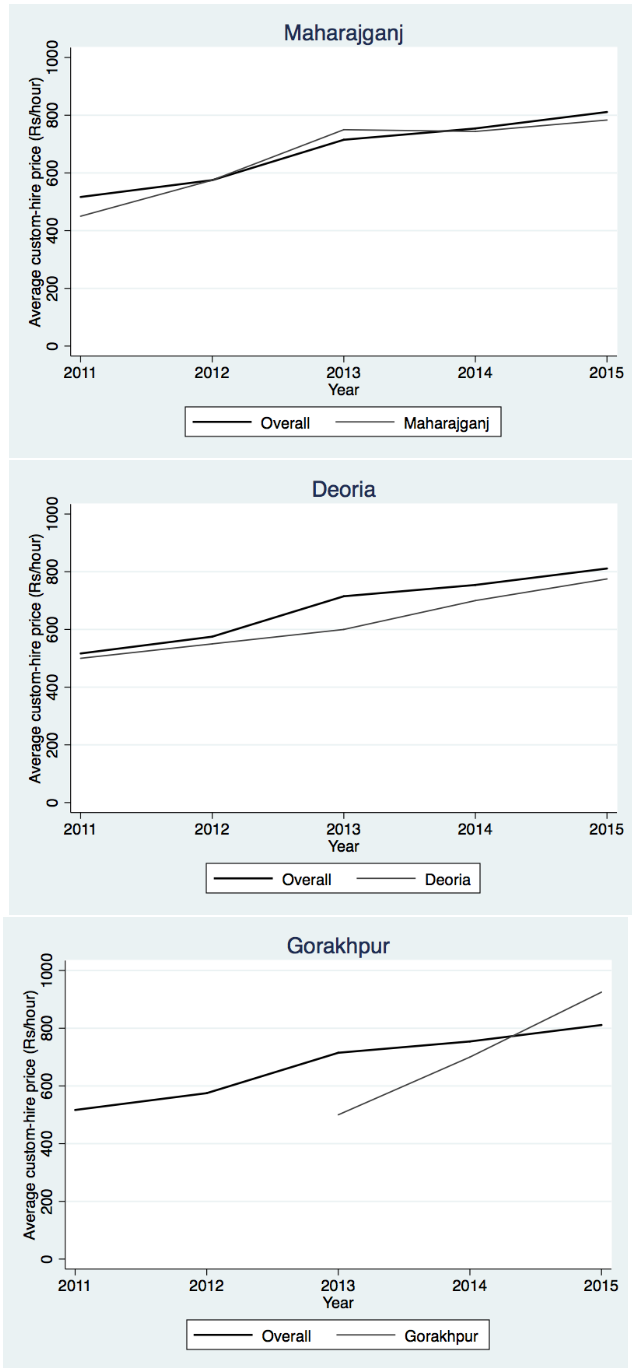

Figure 6: LLL Adoption Increases as the Stock of Service Providers Rises

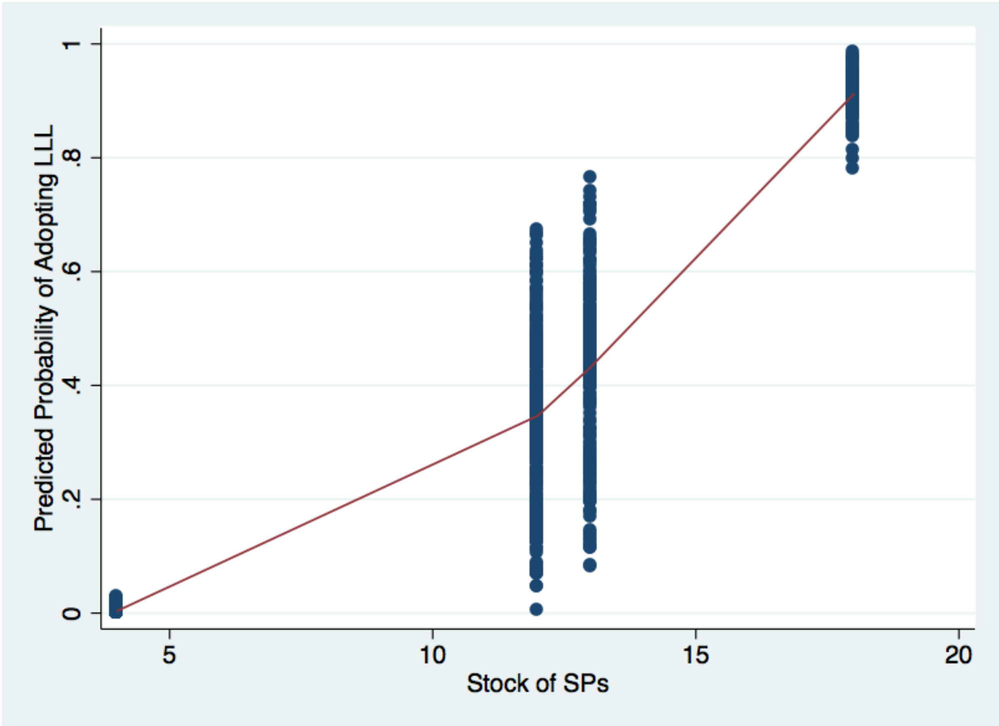

Table 1: Initial LLL Adoption Due to Program Intervention

District	Area Leveled in 2011 (Acres)	Adopters in 2011	Area Leveled in 2012 (Acres)	Adopters in 2012
SAMPLE VILLAGES				
Maharajganj	42.7	47	46.1	34
Gorakhpur	56.9	42	11.5	10
Deoria	119.0	54	70.5	27
OUT OF SAMPLE HOUSEHOLDS				
Maharajganj			24.5	25
Gorakhpur			5.6	5
Deoria			0.7	1

Table 2: Spatial and Temporal Diffusion of LLL Across Villages

Year	Adopting Villages			Service Providers		
	Stock	Average Distance (kms)	Closest Distance (kms)	Stock	Average Distance (kms)	Closest Distance (kms)
2010	10.00	55.88	15.44	2.00	65.28	37.96
2011	21.00	61.43	13.46	3.00	58.34	27.13
2012	27.00	60.72	10.16	4.00	54.72	28.01
2013	99.00	53.93	4.53	12.00	54.48	10.61
2014	184.00	55.54	3.48	13.00	55.51	11.35
2015	288.00	59.11	2.16	18.00	58.32	6.53

Table 3: Laser Land Leveling Cost Structure

	Obs	Mean	Std. Dev.
Purchase Price (Rs.)	20	307050	111439.6
Government Subsidy on LLL Purchase (Rs.)	20	91250	76637.82
Machine Operating Days	19	75	34.64
Driver Cost Per Day (Rs./Day)	18	773.89	1403.14
Operating Cost Per Day (Rs./Day)	16	2131.34	1049.77
Transportation Cost Per Day (Rs./Day)	17	401.76	102.12
Repair Cost Per Season (Rs.)	19	821.05	2288.76

Table 4: Descriptive Characteristics of Adopting Villages

Variable	**Mean**	**Std. Dev.**	**N**
Total households	361.61	311.93	275
Black topped road (=1)	0.78	0.42	274
Net area sown (in hectares)	169.71	156.97	275
Percent area irrigated	83.83	20.81	272
Percent area not irrigated by canal/lake	37.75	45.49	270
Number of cultivators	5.48	4.88	275
Village grows rice (=1)	0.63	0.48	275
Village grows wheat (=1)	0.61	0.49	275
# of prog. vill. within 10 kms radius	1.28	1.34	275
Closest prog. vill (kms)	10.11	6.01	275

Table 5: Adoption of Laser Land Leveling in EUP

Dependent Variable = Adoption in time t {0,1}	(1) LPM	(2) LPM	(3) Probit	(4) Probit	(5) OP Estimates
Access to Road (=1)	0.04682**	0.05379**	0.05583**	0.05434**	0.02446
	(0.022)	(0.027)	(0.025)	(0.027)	(0.018)
Net Area Sown (in Hectares)	0.00005	0.00006	0.00006	0.00006	0.00008
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Percent Irrigated	-0.00122**	-0.00144**	-0.00156***	-0.00150***	-0.00096**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
% Irrigated Not Under Canal/Well	0.00001	0.00011	-0.00016	-0.00007	-0.00007
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% of Agricultural Population	0.00353*	0.00417*	0.00345*	0.00338*	0.00408***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Village Grows Rice (=1)	0.02070	0.02938	-0.00233	0.00410	-0.01076
	(0.020)	(0.025)	(0.025)	(0.026)	(0.017)
# of Program Villages Within 10 kms	0.01060	0.00853	0.01040	0.00404	0.00778
	(0.011)	(0.013)	(0.013)	(0.013)	(0.009)
Dist. to Closest Program Village (kms)	0.00492	0.00267	0.00711*	0.00362	0.00058
	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)
Stock of Service Providers	0.05632***	0.02223***	0.06328***	0.03671***	.04285***
	(0.002)	(0.004)	(0.005)	(0.007)	(0.0036)
Distance to Closest SP (kms)	-0.00121**	-0.00155***	-0.00780***	-0.00670***	-.0022***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.0004)
Lagged Stock of Adopters		0.00334***		0.00141***	
		(0.000)		(0.000)	
Lagged Dist. to Closest Adopting. Vill.(kms)		-0.00489**		-0.00452**	
		(0.002)		(0.002)	
Constant	-0.27817***	-0.05434			
	(0.072)	(0.090)			
Observations	792	792	792	792	792

All standard errors are clustered at the village-level. Specification 5 has bootstrapped standard errors clustered at the village-level

Marginal effects shown for specification (3) and (4) in the probit specification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$