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**The Impact of India's Rural Employment Guarantee on  
Demand for Agricultural Technology**

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## ABSTRACT

The Mahatma Gandhi National Rural Employment Guarantee Act (NREGA) is approaching eight years of implementation. Since 2006, it has offered up to 100 days per year of guaranteed public works employment to tens of millions of rural Indian households. It is intended to augment the purchasing power of the rural poor during droughts and slack agricultural production periods. Given its scale, it has the potential to generate additional ripples throughout the rural economy. Recent working papers have explored NREGA's effect of higher agricultural wages. This paper investigates whether this increase in the opportunity cost of agricultural labor incentivizes farm owners to adopt labor-saving agricultural technology. Using a regression discontinuity design and new Indian agricultural census data, this paper finds that NREGA causes a shift of roughly 20 percentage points away from labor-intensive technologies toward labor-saving ones, particularly for small farmers and low-powered technologies. This short-run result can lead to a variety of long-run outcomes in technology use, labor markets, and food security. A focus on education, skill development, and quality infrastructure alongside NREGA would augment the chances that the most positive long-run scenario occurs.

Keywords: technology adoption, labor markets, poverty, NREGA, India

*JEL codes: H53, J20, O12, O33, Q12*

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# 1. INTRODUCTION

Landless agricultural laborers and small farmers constitute the majority of India's poor. As the rural population continues to grow and more people enter the country's expanding rural labor force, they must eke out a living in the rural sector or add to the growing pressure on urban areas. Meanwhile, rural work is scarce and wages for the poorest have been persistently below official subsistence levels. The Mahatma Gandhi National Rural Employment Guarantee Act (NREGA) aims to alleviate some of these concerns by providing yearly public works employment to rural households at minimum wages.

Passed into law in 2005 and first implemented in 2006, NREGA guarantees any Indian household up to 100 days per year of rural public works employment within 5 kilometers of residence and 15 days of application. Remuneration depends on state-specific minimum wages, usually about US\$2 per day. The law is modeled after the Maharashtra Employment Guarantee Scheme of the 1970s and 1980s, and seeks to increase the purchasing power of the poor during droughts and slack agricultural production periods, when unskilled workers work fewer days and face higher food prices. NREGA projects have focused primarily on water and road infrastructure, and nearly half of all workers have been women—far surpassing the 25 percent quota set by the government at the outset of the program.

Recent working papers have used district-level panel data from India's National Sample Survey and Ministry of Agriculture to find difference-in-differences estimates of 3–5 percent increases in unskilled agricultural wages across the country due to NREGA (Imbert and Papp 2013; Berg et al. 2012; Azam 2012). Shah (2012) further found a 30 percent reduction in wage sensitivity to farm production shocks for every 1 standard deviation increase in the NREGA infrastructure that workers must build. Wage increases are biased toward women and lead to higher overall rural labor force participation rates (Azam 2012; Zimmermann 2012), though it is not clear whether there is crowding out of private-sector jobs. These studies, as well as that of Liu and Barrett (2013), indicate that the program is well targeted to poor laborers.

This paper extends the analysis within the agricultural sector by focusing on how NREGA's effects on rural labor markets alter technology adoption decisions by farm owners. Since farm owners depend on the unskilled labor targeted by NREGA, a change in a worker's wage may affect the input price ratio faced by the farmer and increase the use of technology that replaces unskilled work. During informal focus groups in small farming areas of eastern Uttar Pradesh in late 2011, I found that some farm owners were uncertain about whether they could hire workers on their fields in the next season for the same wages they had paid before NREGA. Laborers, on the other hand, explained that they receive higher wages for some farm tasks while other tasks were simply no longer available. These reports suggest labor-saving technology adoption may favor some agricultural production tasks over others.

This paper incorporates rising unskilled worker opportunity costs into a farm size threshold technology adoption model, which predicts that for relatively small wage increases such as these, the smallest farms will be the most likely to adjust their technology inputs in response to the program. It analyzes outcomes for a range of agricultural technologies and finds that the switch is most likely to occur for farms initially moving from labor-intensive technologies to low-powered labor-saving ones but not for farms moving to more labor-saving technologies. For example, NREGA may drive up the cost of hiring unskilled workers to hand plow a field. In response, the farmer adopts a low-powered, animal-drawn wooden plow that requires fewer—but more highly skilled—workers. However, the model does not predict changes between two labor-saving technologies, such as a power tiller and a tractor-drawn plow, both of which rely less on unskilled labor than would a hand plow.

To test adoption empirically, this study uses a regression discontinuity design that takes advantage of the progressive rollout of NREGA to the poorest districts of the country first. India's Planning Commission ranked 447 districts in its Backwardness Index and implemented the program in the first 200 of these during Phase I in 2006–2007. The next 150 were included as part of Phase II in mid-2007 and the rest of the country in mid-2008. This arbitrary Phase I cutoff allows one to argue that the districts on either side of the 200th rank are similar in observable and unobservable aspects aside from NREGA eligibility.

The study uses a fuzzy design because some districts did not end up in the treatment and control groups according to their ranking.

The paper uses data from the Indian Agricultural Census Input Survey (ACIS), which records farm technology use for hand-, animal-, and machine-powered implements. ACIS data were collected in mid-2007, when NREGA's first phase was drawing to a close, timing that makes it possible to use the districts on either side of the Phase I cutoff as treatment and control groups. ACIS data contrast with the more widely used National Sample Survey released in 2009. Because the latter contains data collected around the Phase II cutoff, it can allow for comparisons only of richer districts. Since I expect technology adoption to occur at the levels of the smallest and poorest farms, it is preferable to use the ACIS data gathered at the time of the Phase I cutoff.

Findings show that NREGA causes a reduction in the percentage of farms using labor-intensive technologies by roughly 20 points and an increase of 15–25 percentage points in the use of animal-drawn technologies. These results imply a decrease in the farm size threshold for basic labor-saving technology adoption due to NREGA. While it is possible that participation in NREGA by small farming households creates income and credit effects that directly boost use of agricultural technology, the labor-saving nature of adoption suggests that at least some of NREGA's impact on technology is channeled through the increased opportunity cost of unskilled labor.

In the long run, continued reverberations between labor, technology, and NREGA in the rural economy can result in a wide range of outcomes. In the best-case scenario, NREGA's positive impact on adoption creates a win-win situation for farm owners and laborers to the extent that the technologies adopted increase farm productivity and the newly created NREGA infrastructure increases market access. In this case, demand for agricultural labor could not only return to pre-NREGA levels but shift out further, leading to higher wages and increased employment (at higher skill levels). With poor-quality infrastructure and low levels of education and skill development, however, laborers could be worse off in a post-NREGA era as labor-saving technology is adopted and neither public works nor agricultural jobs are available. Even in this worst-case scenario, though, the prevalence of custom-hire technology markets increases the chances that farmers can disadopt technology and labor and that technology markets can return to pre-NREGA equilibria. New data will enable future testing of these competing long-run scenarios.

Finally, the analysis explores whether NREGA's focus on water-related public infrastructure impacts adoption of water-saving technologies. It shows that NREGA not only significantly reduces the use of private diesel pumps—one of the most popular methods of agricultural water extraction—but also reduces the use of water-conserving technologies, such as sprinkler and drip irrigation systems. Thus, NREGA has an important, albeit indirect, role in influencing both labor-saving and water-conserving agricultural technology adoption through its wage payments and choice of public works. Policymakers may want to consider these technology adoption incentives vis-à-vis their rural development priorities as they move forward with changes to NREGA and creation of other rural poverty programs inside and outside of India.

The rest of this paper is structured as follows. Section 2 provides the motivation and structure of NREGA and reviews the literature related to the employment guarantee's impact on labor and technology markets. Section 3 develops a farm size threshold model of adoption that ties increases in the opportunity cost of agricultural labor with the adoption of labor-saving technology. Section 4 discusses empirical methodologies, and Sections 5 and 6 detail the data and results, respectively. Section 7 concludes.



## 2. BACKGROUND

This section first describes in more detail the motivation behind NREGA and its specific poverty-related goals. It then looks more closely at the literature related to agricultural wage responses to an employment guarantee, including an earlier set of studies revolving around a 1970s state-level employment guarantee in Maharashtra as well as recent studies on NREGA's agricultural wage effects. The next subsection discusses the state of the literature on determinants of technology adoption, specifically those pertaining to labor-saving technologies. In general, recent studies have not focused on the role of labor market changes in determining labor-saving technology adoption. The section ends with a review of the literature on how both the quantity and the quality of village infrastructure investment affect labor and technology markets in helping determine long-run outcomes.

### **The Mahatma Gandhi National Rural Employment Guarantee Act**

NREGA offers local wage employment for public village development projects, guaranteeing every unskilled laborer 100 days of public works employment in his or her own village at a wage of at least 100 Indian rupees per day. This employment guarantee is not the first program of such a scale to take place. Conditional cash transfers (CCTs), such as Bolsa Familia and Oportunidades, and the Public Distribution System, have taken place in Brazil, Mexico, and India, respectively. Utility theory suggests that in-kind transfers are less efficient in raising the utility of the poor than direct cash transfer programs, which let the targets of the programs decide how to spend all of their income. However, there have been concerns about the long-term outcomes of program beneficiaries, especially in the areas of health and education. Therefore programs like Oportunidades combine a cash transfer with in-kind assistance by directly transferring money to beneficiaries and attaching conditionalities to the transfer, such as attendance at school or regular family health checkups.

Although NREGA is a public works employment program, it can also be thought of as a sort of CCT that transfers money directly to laborers conditional on fulfillment of a requirement. Whereas in Oportunidades the requirements are school attendance, health clinic visits, and nutritional support, a NREGA unskilled laborer must work on infrastructure development projects in his or her own village. In the same way that CCTs like Oportunidades aim to shape specific long-term outcomes such as education and health through cash transfers, NREGA focuses on improving village infrastructure as a public good. Workers are able to physically develop their own villages and pave the way for economic growth and poverty reduction at home. Several studies have discussed the impacts that infrastructure development can make on the economies of marginalized villages (de Janvry et al. 1991; Binswanger et al. 1993; Fan, Hazell, and Thorat 2000; Narayana et al. 1988).

Besides rural infrastructure development, NREGA directly aims to achieve three broader goals in rural areas. The first, and according to the government the most important, is to enhance the purchasing power of poor laborers. Dreze (1990) studied closely a government response to the severe drought in Maharashtra from 1970 to 1973 known as the Employment Guarantee Scheme (EGS), and concluded that diminishing purchasing power by the poor in the face of famine was of larger concern than actual limitations in food availability due to market imperfections. In a review of the history of famines in India, Drèze cited a 19th-century report, noting “the first effect of drought is to diminish greatly, and at last to stop, all field labor, and to throw out of employment the great mass of people who live on the wages of such labor” (1990, 17). Drèze continued, “even today it is clear that the high level of market integration in India would be of little consolation for agricultural laborers if government intervention did not also protect their market command over food during lean years” (1990, 25). NREGA guarantees work to laborers who either lose their seasonal work in bad years or simply cannot make ends meet during typical slack agricultural production periods, when work is low. Thus, in addition to guaranteeing a job, NREGA also pays minimum wages to ensure that the poor maintain their purchasing power in bad seasons.

A second goal of NREGA is the enforcement of minimum wages in rural areas. The Indian Minimum Wages Act of 1948 was created to ensure a subsistence wage for workers, with each state of India determining its own minimum income needed to stay out of poverty. The legal wage is increased at least every five years to keep up with subsistence requirements in real terms. In rural India, however, the structure does not exist to ensure or enforce the payment of minimum wages, especially on farms. Moreover, with an economic environment that can change quickly along with increasing volatility in food prices, the minimum wages themselves are often not updated frequently enough. NREGA incentivizes payment of the minimum wage by covering the wages of unskilled workers using the federal budget while putting the onus on local governments to cover unemployment benefits for those in their constituency. Local governments, thus, have a financial incentive to implement NREGA and keep unemployment low in their villages.<sup>1</sup>

Finally, NREGA tried to incorporate methods from the Maharashtra EGS to deal with targeting and selection issues in this transfer program. The EGS was able to target those most vulnerable to drought-related income collapses by locating offices in rural areas and requiring regular attendance. This way, officials could be sure that those with the lowest opportunity costs would select themselves into the treatment, ensuring the objectives of both getting aid to those who were at highest risk of starvation and avoiding elite capture.<sup>2</sup> Thus, the structure of NREGA reflects the successes and lessons of the Maharashtra EGS, particularly in the types of works undertaken and the method of implementing the program.

## **Employment Guarantee and Agricultural Labor Markets**

Though the theoretical literature on guaranteed employment and rural labor impacts is scarce, ongoing empirical analyses of NREGA's effects in the labor market have shown mixed results, with most studies estimating positive impacts on agricultural wages due to NREGA. For example, Imbert and Papp (2013) found both a 5.5 percent increase in agricultural wages and a crowding out of private-sector employment. Berg et al. (2012) found a roughly 3 percent increase in agricultural wages with about 6–11 months for this impact to manifest itself on farms that hire casual labor. Azam (2012) saw an 8 percent increase in female agricultural wages but only 1 percent for men.

All these studies used difference-in-differences estimation to find increases in agricultural wages of between 3 and 5 percent, while highlighting private-sector impacts only during the dry season and gender neutrality in impact distribution. Shah (2012) estimated a 6.5 percent increase in agricultural wages and additionally found that a 1 standard deviation increase in infrastructure development due to NREGA led to a 30 percent reduction in wage sensitivity to production shocks. Zimmermann (2012) used a regression discontinuity design, finding agricultural wage increases for women only during the main agricultural season and no effect on private employment so no change in labor force makeup.

Most of these studies did not develop theoretical models explaining how an employment guarantee should impact agricultural wages. Of those that did, Imbert and Papp (2013) drew heavily from earlier models showing the distributional effects of price changes on consumption goods by replacing the latter with labor markets. Zimmermann (2012) used a simple minimum wage model and added labor rationing to generate the hypothesis of increased agricultural wages.

During India's original employment guarantee in Maharashtra in the 1980s, most studies of the effects were theoretical and not empirical. Narayana et al. (1988) stylized the Indian agricultural labor market by separating demand according to peak and lean season. They then showed how the EGS changes the market (Figure 2.1). The amount of labor up until point  $L$  is the labor supply available to work at the going lean-season wage,  $w_L$ . Before the EGS, the only demand for rural labor is assumed to be for

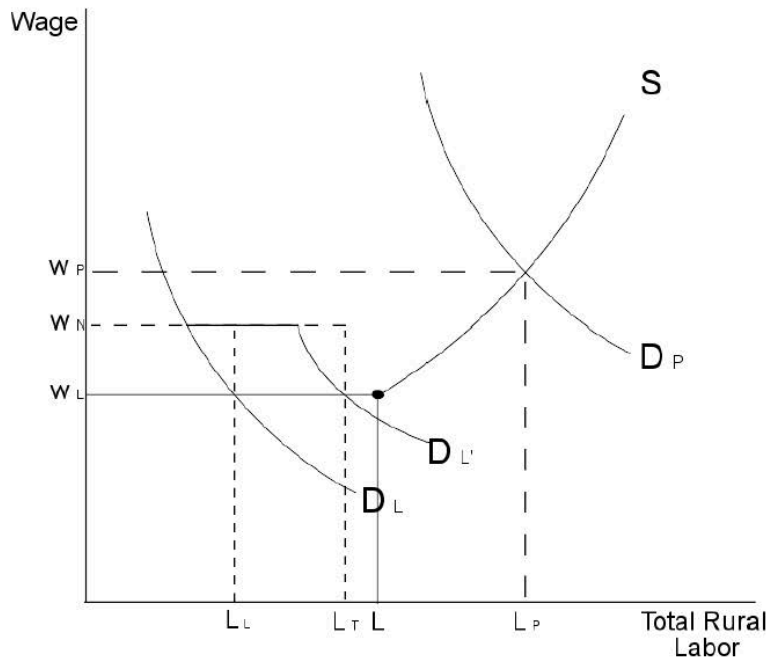
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<sup>1</sup> Wage seekers have the right to an unemployment allowance from their local governments in case NREGA employment is not provided within 15 days of submitting the application or from the date when NREGA work is sought.

<sup>2</sup> Narayana et al. (1988) also discussed the topic of elite capture in the EGS and showed that a program carried out efficiently, targeted effectively, and financed properly is effective in alleviating poverty in India.

agricultural purposes. With the lean-season labor demand curve,  $D_L$ , workers are hired only until point  $L$ , leaving  $L - L_L$  excess labor in the lean season (and full employment at  $L_P$  in the peak season). With a limited employment guarantee, total lean-season labor demand now shifts out to  $D_{L'}$ , putting the total lean-season labor equilibrium at  $L_T$ . One can see that in this analysis, whether or not agricultural wages increase is inconclusive and depends on the magnitude of the shift in  $D_L$ . As long as  $L_T$  is less than  $L$ , that is, excess labor is not totally exhausted by the public works program, there will be no effect on agricultural employment (still at  $L_L$ ) or workers' agricultural income ( $L_L \times w_L$ ). But workers will now be gaining  $(L_T - L_L) \times w_P$ , where  $w_P$  is the officially set public works wage. The peak-season equilibrium ( $L_P, w_P$ ) is also unaffected.<sup>3</sup>

**Figure 2.1 Agricultural and NREGA labor supply with peak and lean season demand**



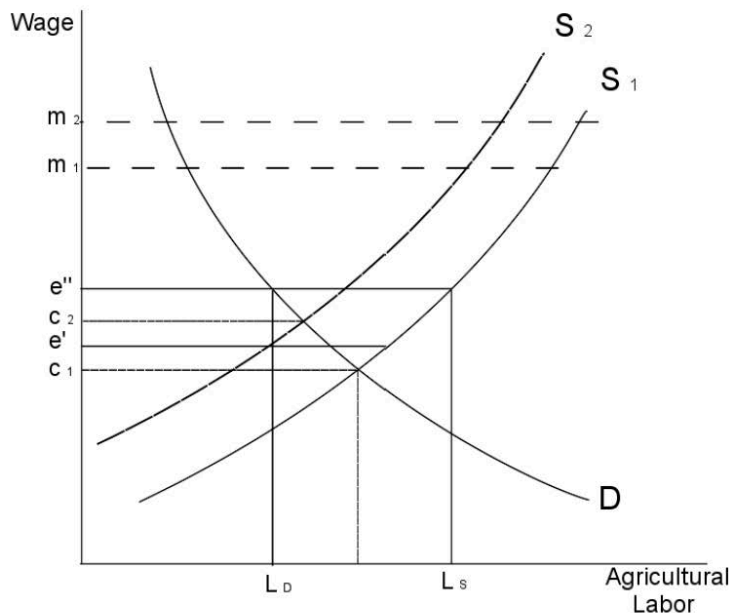
Source: Narayana et al. (1988)

Osmani (1990) saw the agricultural wage determination process in India differently. He argued that farm workers collectively determine the equilibrium wage via repeated wage-setting games. The equilibrium wage becomes higher than the competitive wage due to this “implicit cooperation.” Workers ask for a wage above their opportunity cost and employ a “trigger strategy” that penalizes any worker who undercuts them by accepting a lower wage. The success of this strategy and the value of the initially requested wage depends on the opportunity income of the worker. A requested wage must be at least higher than what one would make outside of agriculture but not so high that a worker would be willing to incur the penalty of the trigger strategy. In the Osmani model, an employment guarantee would serve as a boost in opportunity income, or increase in  $c_1$  to  $c_2$  (Figure 2.2). This pushes up Osmani’s equilibrium wage interval, which has  $c$  as its lower bound. But it is not clear if this changes  $e$ . The equilibrium wage is characterized either by an interior solution within the wage interval or the maximum interval value,  $m$ . If the original wage is an interior solution to  $(c_1, m_1)$ , such as  $e''$ , then a boost in the opportunity income to  $c_2$  does not necessarily have an effect on the equilibrium wage. If the original solution was  $e'$ , however, the agricultural wage will get pushed up from  $e'$  to at least  $c_2$ . A third scenario is if the equilibrium wage is

<sup>3</sup> Even in the case where  $w_P \leq w_N$ , there should still be no effect on the peak agricultural labor market because both EGS and NREGA intend employment to be offered only during the lean agricultural season.

initially the maximum value of the interval,  $m_1$ , and then can either stay there or move to  $m_2$  with the change in opportunity income. Osmani cited several factors that determine this interval and where exactly the equilibrium wage falls, including a worker's time discount factor and subjective probability of employment.

**Figure 2.2 Implicit cooperation amongst workers leads to equilibrium wage above competitive wage**



Source: Osmani (1990).

Basu (2011) developed a theoretical model of an employment guarantee that predicted impacts on output and labor markets. His model featured a mutually exclusive choice by laborers to work either in a year-round permanent contract with a landlord or as both a public works employee during the lean season and a casual agricultural laborer during the peak season. He found that (1) an increase in the public works wage results in a decrease in agricultural labor and an increase in the casual wage rate, if certain public and private productivity levels are met, and (2) a technological improvement can also increase the casual wage rate. Although Basu was able to conclude that agricultural wages increase due to an employment guarantee, the results are greatly dependent on a highly stylized specification of the Indian labor market. The existence of permanent labor is important in the model, but it is not necessarily applicable to all rural Indian contexts, especially the poorest ones. The author also assumed that workers cannot perform lean-season agricultural work and public work at the same time.

Nevertheless, Basu did use his model to consider the impact of an EGS on agricultural employment and wages under different labor market specifications. For example, he showed that a landlord's being confronted with a minimum wage,  $\bar{w}$ , but simply wanting to pay workers their reservation wage,  $w_r$ , will result in a game-theoretic problem between two types of workers, high-wage and low-wage workers, both of whom are represented by separate labor unions that can contest agricultural wages against each other in a noncooperative way. This is an extension of Osmani's implicit cooperation model. But again it is highly stylized: the existence of labor unions was mainly specific to Kerala at that time and not generalizable to the Indian context as a whole, especially poorer states. The game-theoretic extension results in upward pressure on agricultural wages. Considering the case of an additional permanent-versus-casual labor distinction, Basu built on previous tied-labor literature to argue that an EGS

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## Technology Adoption

The literature on determinants of technology adoption has evolved substantially over the last few decades. Three survey studies capture the transition. Feder, Just, and Zilberman (1985) reviewed technology adoption models that discuss the role of land tenure, farm size, uncertainty, and information. The authors cautioned against a trend in the literature at the time of “nonexistence of government policies in most adoption models” (1985, 288), which can affect relative input and output prices and, thereby, technology choices. Besley and Case (1993) critiqued time-series adoption models for being too broad in nature and less useful than other methods for determining individual adoption practices. But they also noted that most cross-section empirical studies ignored adoption dynamics and focused only on the correlation between farmer characteristics and final adoption. The authors suggested a more a balanced approach and highlighted dynamic optimization studies that modeled state dependence between periods and tested adoption practices using panel data. They concluded that most of the previous studies did not account well for factors such as information and access to credit. Finally, Foster and Rosenzweig (2010) highlighted in their more recent survey on technology adoption other important adoption constraints, including credit, insurance, information, economies of scale, risk preferences, and behavioral processes.

Most of these surveys and studies have not explicitly addressed the role of labor availability in technology adoption. Hicks and Johnson (1979) and Harriss (1972) examined the effect of high and low rural labor supplies, respectively, on the adoption of labor-intensive technologies, but the effect of either of these on labor-saving technologies has not been rigorously studied with data. Empirical evidence cited by Feder, Just, and Zilberman (1985) demonstrated that uncertainty in the availability of labor does indeed lead to the adoption of labor-saving technologies. And Spencer and Byerlee (1976) examine technical change and labor use in a farming area of Sierra Leone characterized by large quantities of land and small amounts of labor. They showed labor supply constraints to be overcome by adoption of mechanical production techniques in rice-growing areas. But it is not clear if the opposite conclusion can be made for the other WVaXZWS` VZSTaddS[a ebWfdg\_ Ii Z[UZ[e\_ adWZSdUW[e]UaXlag` fdW`[] W`  
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The role of labor availability was an important topic in earlier studies of technology adoption. But the discussion of determinants has moved away from this subject and toward previously lesser known issues such as finance, information, and risk. Empirical work on technology adoption has thus shifted toward changes in these explanatory variables and consequently found interesting results with many policy implications. The present research fills a gap in recent literature by reexamining and re-modeling the role of labor availability in technology adoption. It begins with threshold models developed by Sunding and Zilberman (2001) and Just and Zilberman (1988) that use changes in (expected) profits as triggers for adoption. These profits are thought of abstractly in these studies with discussion often alluding to changes or uncertainty in output prices or learning. This paper develops the threshold model to explicitly account for changes in labor markets and to restrict the outcome to labor-saving technologies in order to capture the theoretical effects of NREGA.

## Infrastructure Investment

The final part of this section reviews some of the literature on infrastructure investment and discusses how it relates to a public works employment guarantee's effect on both agricultural labor markets and technology adoption in the long run.

Binswanger, Khandker, and Rosenzweig (1993) looked at links between investment decisions of governments, financial institutions, and farmers in 85 districts across 17 states in India. They measured both the impact of investment by these entities on infrastructure development and the joint impact of all investment on agricultural output and productivity using district-level, time-series data. Addressing the simultaneity of infrastructure improvements, financial investment, and agroclimatic variables, the authors used fixed effects to identify the impacts of roads, primary schools, and electrification on agricultural output growth, showing significant positive effects of 7, 8, and 2 percent, respectively. Private investment, such as on tractors, fertilizers, pumps, and animal purchases by farmers, showed mixed effects. Farmers' use of tractors increased 6 percent due to canal irrigation, whereas roads improved agricultural output by 6.7 percent. These investments were both significant in affecting both agricultural input use and output levels, as well as encouraging private investment. Fan, Hazell, and Thorat (2000) showed that rural roads and agricultural research had the highest per-rupee impact on poverty and productivity growth in India, with only modest impacts from irrigation, soil and water conservation, health, and rural and community development.

de Janvry, Fafchamps, and Sadoulet (1991) focused on the transaction cost wedge of rural villages and showed pathways through which physical rural development can benefit the poor. These authors addressed the seeming paradox that peasant farm households do not respond to price changes in a way that is consistent with traditional economic theory and argued that it is the lack of infrastructure that keeps transaction costs high, preventing price changes from reaching the most marginalized villagers. With a reduction in these transaction costs through infrastructure development, rural households will be more responsive to changes in their economic environment.

Narayana et al. (1988) released a study around the same time as Dreze's post-Maharashtra EGS analysis that looked at the potential of rural works programs in India that are similar to those of NREGA in that they provide work opportunities in roads, irrigation, and school building to unskilled labor during slack agricultural seasons. The authors showed, using a sequential general equilibrium model, that these programs do not necessarily jeopardize long-term growth and can be effective in alleviating poverty. In addition to creating "demand for perhaps the only endowment the rural poor have, namely, unskilled labor," rural works programs, that authors claimed, "also improve rural infrastructure, thereby increasing productivity of land" (1988, 153).

### 3. MODEL

This section brings labor and technology markets together to determine the theoretical short-run effects of NREGA. The model shows how a rural works program that raises agricultural wages impacts farm owner decisions in the technology sector by reducing the minimum farm size needed to cross the adoption threshold.

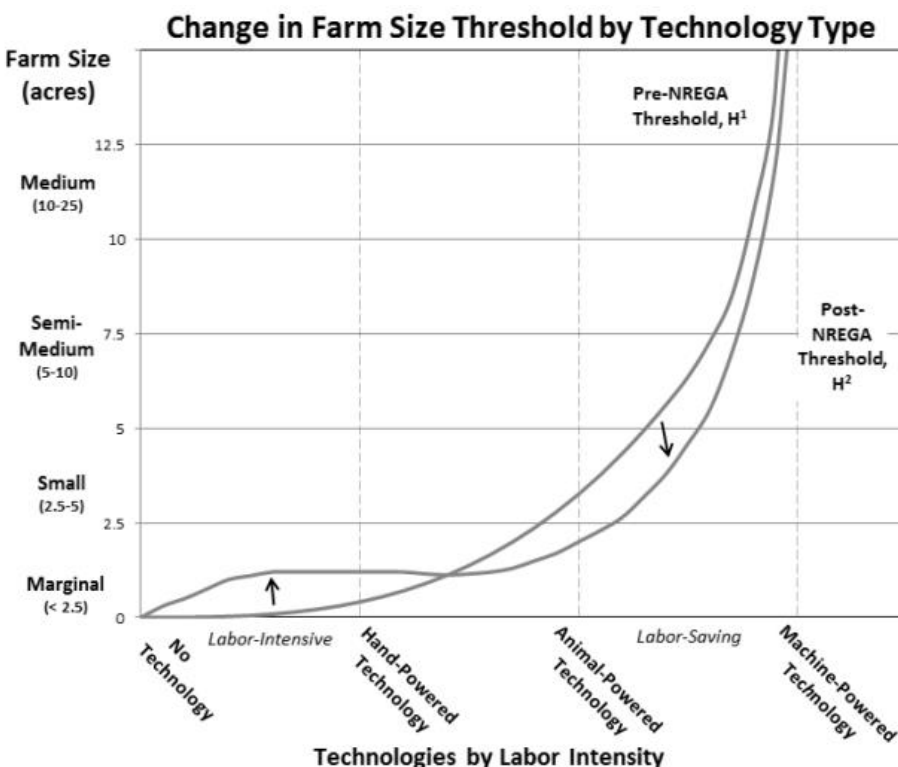
#### Threshold Model of Technology Adoption

The farm size technology adoption threshold of Sunding and Zilberman (2001) shows one channel through which technology adoption may occur, linking NREGA, agricultural wages, and technology adoption. Though the threshold model is intended to describe diffusion over time, it can also capture farmer heterogeneity of technology adoption at a given point in time. Adoption takes place above a certain cutoff farm size,  $H_j^c$ , which depends on fixed costs,  $F_j$ , and the difference in profit,  $\Delta\pi_j$ , for technology  $j$  compared with the incumbent technology:

$$H_j^c = F_j / \Delta\pi_j. \quad (1)$$

Figure 3.1 shows a pre-NREGA farm size threshold curve that increases in  $F$ , keeping  $\Delta\pi$  constant across all technologies  $j$  for simplicity. The technologies that increase with  $F$  are categorized on the x-axis as hand-, animal-, and machine-powered technologies. Due partly to the active custom-hire technology markets in India, much of the fixed cost of technology adoption captures information and learning. Thus, there is little or no fixed cost near the origin, where farmers use no technology or the most basic hand-powered implements, while machine-powered implements, such as combine harvesters or direct-seeded rice, require the most information and learning.

**Figure 3.1 The technology adoption threshold increases for labor-intensive technologies and decreases for labor-saving technologies due to NREGA**



Source: Author.

In the denominator of equation 1, let us explicitly incorporate the opportunity cost of agricultural labor,  $w^A$ , to obtain

$$H_j^c = F_j / [\pi_j^1(p, Q, w^A, L, r, K) - \pi_j^0(p, Q, w^A, L, r, K)]. \quad (2)$$

Assuming  $F$  does not change due to NREGA, then the effect of the program will show up via  $w^A$  and, consequently, through  $\Delta\pi_j$ , where  $\pi_j^1$  is the profit when adopting technology  $j$  and  $\pi_j^0$  is profit from using the incumbent technology associated with technology  $j$ . The largest changes in  $\Delta\pi_j$  (and, therefore, on  $H_j^c$ ) will occur for technologies closer to the origin of Figure 3.1, that is, when a farmer switches either from no technology to a labor-intensive one or from a labor-intensive technology to a labor-saving one. This is because in these cases  $\pi_j^1$  and  $\pi_j^0$  will provide the most separation from each other as  $w^A$  changes.

As an example, for a farmer considering using many workers equipped with hand hoe technology to turn over soil on a field, an increase in  $w^A$  due to NREGA causes  $\pi_{hand\ hoe}^1$  to decrease, since profits under a labor-intensive technology are highly dependent on agricultural wages, and  $\pi_{hand\ hoe}^0$  to be unaffected, since agricultural wages are not being paid for a fallow plot. Thus,  $\Delta\pi_{hand\ hoe}$  decreases by the change in  $\pi_{hand\ hoe}^1$  from the period before NREGA to the period after. A farmer already employing workers with hand hoes and considering a switch to a labor-saving animal-drawn wooden plow will observe a slight decrease in  $\pi_{wooden\ plow}^1$  since labor-saving technology is relatively less dependent on agricultural wages, and a large decrease in  $\pi_{wooden\ plow}^0$ , or the profit under the wooden plow's incumbent technology, hand hoes, due to higher unskilled wages resulting from NREGA. As the farmer moves further along the x-axis, the relative changes in profits from new technologies will decrease as the technologies under consideration become less dependent on unskilled agricultural wages.

The effect on the farm size threshold for various technologies is shown in the post-NREGA curve in Figure 3.1. For hand-operated implements, the farm size threshold increases, making adoption more difficult for small farmers. For animal-powered implements, the farm size threshold decreases because higher wages make labor-saving technology more profitable and labor-intensive operations more expensive. The change in profits when adopting machine-powered implements to replace animal-powered ones is likely to be the smallest when NREGA's impact is channeled only through agricultural wages. Although using a tractor to plow one's field is arguably more profitable than using oxen, this difference in profit does not likely change due to higher agricultural wages, as compared with choosing oxen over a field full of workers with hand hoes. So the change in the farm size threshold for machine-operated implements due to NREGA's impact on wages is not likely to be very high.

One benefit of the threshold model in which farm size is the cutoff for adoption is that it is flexible enough to describe both large and small farm areas, an important variable in the Indian context, where the vast majority of farms are small and many technology adoption studies are done in the large farm context only. However, since fixed costs are mostly held constant in this analysis, it is possible to show a similar result on small farm technology adoption without them, such as in a labor-cost supervision model. The next section discusses the empirical approach for testing these theoretical implications.



## 4. EMPIRICAL STRATEGY

There are several approaches one could use in estimating NREGA's effect on technology adoption. This study first considers ordinary least squares (OLS) but argues that endogeneity of technology adoption decisions with NREGA treatment will lead to biased results, since the poorest districts received the program in the first phase. Most NREGA studies have relied on difference-in-differences to identify causal impacts on other outcomes, such as agricultural wages and nutrition. This study considers both a general difference-in-differences specification and a fixed effects model. This paper discusses the validity of these estimates given the nonrandom assignment of NREGA across districts. Finally, it presents a regression discontinuity design that, in contrast to OLS and difference-in-differences methods, takes advantage of the progressive rollout of the program by evaluating differences in outcomes at the arbitrary Phase I treatment cutoff.

### Ordinary Least Squares

In order to obtain a first rough estimate of the impact of NREGA on technology adoption, let us consider a simple OLS model with district-level controls:

$$TA_{it} = a + b * NREGA_{it} + \gamma * X_{it} + e_{it}, \quad (3)$$

where  $TA$  is the percentage of farms in district  $i$  using any labor-saving technology in year  $t$ ,  $NREGA$  is a binary indicator of whether district  $i$  received NREGA in year  $t$ , and  $X$  is a vector of district-level controls. This model will capture the effect the NREGA program has on technology adoption in district  $i$  if the expected value of the error term is zero, or  $E(e_{it} | X_{it}) = 0$ . However, this is unlikely to be the case if districts that are more likely to adopt the technology are also less likely to be poor and, therefore, also less likely to participate in the first phase of NREGA. The econometric concern is endogeneity, whereby technology levels in the district also determine whether the village is likely to receive NREGA treatment. There is also a high chance of serial correlation in outcomes over the years before and after implementation of NREGA.

OLS estimates of the effect of NREGA participation on technology adoption ultimately will be biased. Two econometric techniques are employed to address this bias: difference-in-differences and regression discontinuity (RD) design, the second of which relies on changes in adoption rates in the districts that were above and below the cutoff index value that determined the dispersal of NREGA funds during the initial rollout. Estimates from these two approaches will be compared with each other and with the OLS approach.

### Difference-in-Differences and Panel Fixed Effects

The difference-in-differences approach compares districts that participated in the first phase of NREGA (the treatment) with those that did not (the control) both before and after the program takes place. The specification is

$$TA_{it} = a + \beta NREGA_{it} \cdot post_t + \gamma post_t + \delta NREGA_{it} + e_{it}, \quad (4)$$

where  $TA$  is the percentage of farms using labor-saving technology in district  $i$  and year  $t$ ,  $NREGA$  is a dummy variable equaling 1 if the district has implemented NREGA in year  $t$ , and  $post$  is a dummy variable equaling 1 for observations after the beginning of the program. Converting the number of farms using technology into a percentage controls for differing numbers of farms in different districts, while right-hand-side specification accounts for both varied initial levels of technology use in districts and general trends over time.

Equation (4) can be improved upon with panel data by including district fixed effects. The panel fixed effects equation is

$$TA_{it} = \beta NREGA_{it} \cdot post + \gamma_t + \delta_i + e_{it}, \quad (5)$$

where now  $\gamma$  is a post-NREGA dummy representing the time fixed effect and  $\delta$  is a district-level fixed effect for each district  $i$ . The main coefficient of interest in Equation 5 is  $\beta$ , which gives the treatment effect of NREGA on technology adoption net of time trends and time-invariant district characteristics.

This within estimator is used to counter the endogeneity concerns of both OLS and a general difference-in-differences specification, since selection into NREGA is not random. The 200 poorest districts that first got NREGA may have unobservable time-invariant characteristics that affect their technology adoption practices. However, there may be time-varying characteristics that do affect groups differently. All previous NREGA studies have found evidence for common trends between the two groups, using placebo tests, cubic and quartic time trends, and a variety of controls. This study does not test for parallel trends, opting instead for an RD approach that does not require the common trends assumption.

### Regression Discontinuity Design

The RD method does not require exogeneity of the treatment variable with the outcome. RD solves the identification challenge by assuming that villages around a treatment threshold are the same in all characteristics except for a certain exogenous factor that assigns the treatment to some and not to others. Lee and Lemieux argued that “in many contexts, the RD design may have more in common with randomized experiments (or circumstances when an instrument is truly randomized)—in terms of their ‘internal validity’ and how to implement them in practice—than with regression control or matching methods, instrumental variables, or panel data approaches” (2009, 292).

The RD equation takes the form

$$TA_i = \alpha + \beta NREGA_i + \gamma rank_i + \delta rank_i^2 + \eta NREGA_i rank_i + \lambda NREGA_i rank_i^2 + e_i, \quad (6)$$

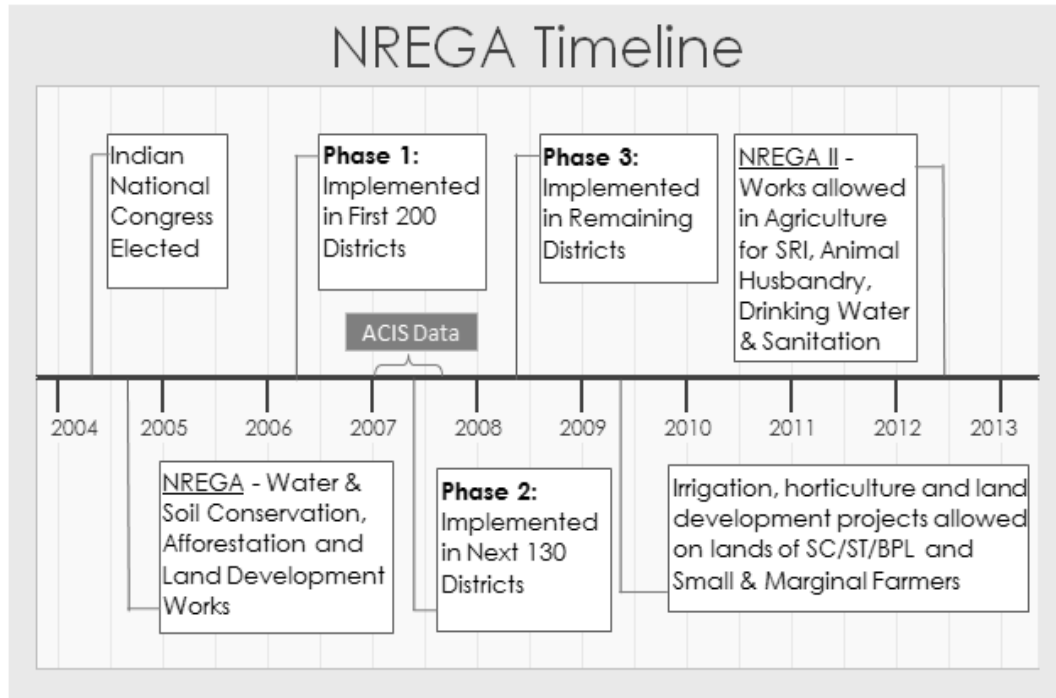
where the dependent variable is the technology adoption rate in district  $i$  after NREGA has been implemented and  $\alpha = TA_0$  is the estimated percentage of non-NREGA farms adopting labor-saving technology at 200-district cutoff.  $\beta = TA_1 - TA_0$  is the treatment effect of interest, and  $rank$  is what determines the cutoffs for each phase based on the Backwardness Index. Some estimations in Section 6 will be conducted with 2004 baseline technology adoption rates subtracted from the dependent variable because of the potential reduction in the estimator’s sampling variability that can occur with the inclusion of pre-random assignment observations on the dependent variable (Lee and Lemieux 2009).

The interaction terms in equation (6) allow the pooled regression function to differ on both sides of the NREGA cutoff, while the squared terms allow a flexible form to be used instead of imposing linearity. Use of RD usually requires that either observations closest to the threshold be appropriately weighted or the window of observations be restricted to the districts that make more natural treatment-control groups, due to similarity in characteristics before the program. This study will weight observations away from the cutoff using a triangle kernel and also consider several windows around the threshold.

RD does not require that the variation in the treatment variable be exogenous to the outcome of interest. It is important, however, that the threshold variable of an RD specification be nonmanipulable by the beneficiaries of the treatment. Manipulation can happen, for example, in the case of government healthcare for low-income individuals, whereby employers may pay individuals slightly less in order to avoid private healthcare costs, thus contaminating the treatment and control groups for comparison on either side of the threshold level of income. In the case of NREGA, the threshold is the Planning Commission’s Backwardness Index, which ranks the 447 poorest districts in India using wages, productivity, and percentage of the population belonging to the scheduled castes and tribes from the early and mid-1990s. The first 200 districts in the index received NREGA funds in 2006, while the next 130 began the program almost two years later (Figure 4.1). Because the government used measures from the 1990s to determine whether villages received NREGA treatment in 2006, this threshold variable does not

appear to be manipulable. Without any knowledge that NREGA would exist a decade later, it would not have been possible for district governments to manipulate their development indicators in the 1990s in anticipation of the program.

**Figure 4.1 The evolution of NREGA**



Source: Author.

Notes: The Indian National Congress party was elected in May 2004 and passed NREGA by the end of the year. The first districts implemented NREGA in February 2006, one and a half years before Phase 2 districts. The primary data used for this study is from 2007. NREGA included mostly just public water- and land-related projects until 2009.

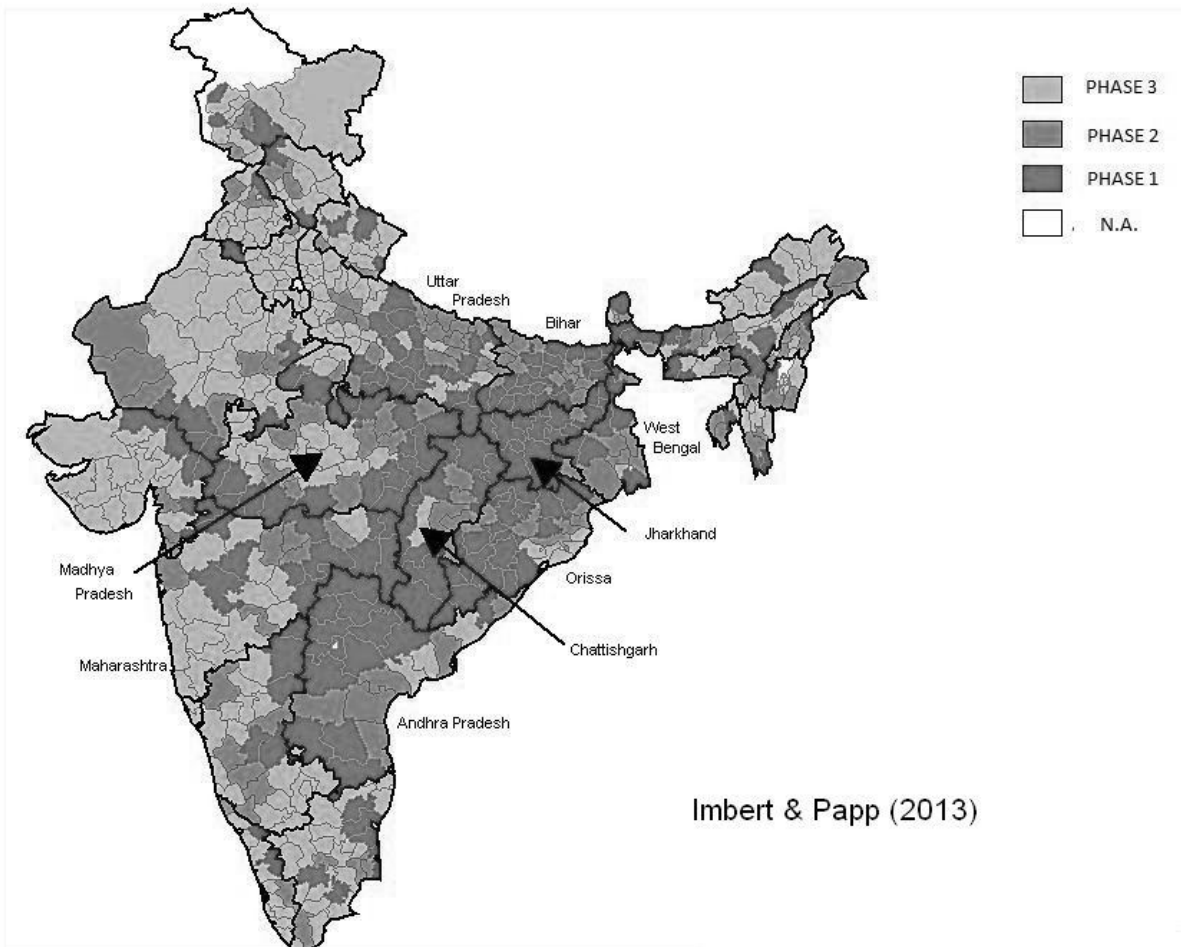
The RD design is fuzzy because, although districts theoretically become part of NREGA in a deterministic way solely dependent on their rank, that is,  $NREGA_i = f(rank_i)$ , and they cannot manipulate the threshold variable, the correlation between ranks under 200 and NREGA participation is not one to one. This is most likely a consequence of many states having been politically assured NREGA participation for their poorest districts, regardless of whether those districts were below the cutoff. These considerations are discussed in more detail below using graphical depictions.

## 5. DATA

The data for this study comes from the Ministry of Rural Development's ACIS. Figure 4.1 indicates when the data were collected. While NREGA was being rolled out in three phases, ACIS was conducted in three periods of its own in 2006–2007. In the first period, the number of farm holdings in each district was recorded and tabulated by size, gender, and social group. At that point, the *tehsil* was randomly selected. A *tehsil* is a block or an administrative unit at the sub-district level consisting of many villages. Each *tehsil* then had 20 percent of its villages randomly selected (100 percent of villages for small states), and finally, the input survey itself was conducted for the farms within the final list of villages, ensuring that each village had at least four farms for each of the five farm size groups: marginal, small, semi-medium, medium, and large. Enumerators enacted this final data collection phase almost one year after starting the process in 2006, placing the actual data collection at early to mid-2007.

Previous studies mostly use 2009 National Sample Survey data, which restricts analysis to comparisons between Phases II and III. Because the present theoretical model predicts impacts at the poorest and smallest farm levels, comparisons at the cutoff between Phase I and Phase II are preferable for this analysis. Furthermore, Phase III districts are likely not the best controls for the poorest districts in the country (those in Phase I), and pooling Phase I and II districts together ignores the fact that Phase I districts received NREGA longer than Phase II districts (Figure 5.1). This analysis uses treatment and control groups consisting of Phase I and Phase II districts in an RD framework, which enables trimming the richest (and absolute poorest) districts in India before estimating impacts at lower levels of development.

**Figure 5.1 The phased rollout of NREGA in India**



This analysis also makes use of the 2004–2005 the India Human Development Survey (IHDS). These data have been used extensively, particularly by sociologists interested in nutrition and intrahousehold decisionmaking in India. They provide another panel for testing short-run technology adoption decisions using difference-in-differences and district fixed effects methods as comparisons with RD results. Both IHDS and ACIS will soon be releasing their next rounds of data, allowing testing of long-run implications of the results generated here.

Table 5.1 shows ACIS data broken down by farm size. Each district in the sample has on average 123,000 marginal farmers, whose total acreage equals 2.5 or less. Despite making up 64 percent of all farms in the district, marginal farmers cultivate only 21 percent of total area. Conversely, the largest farmers in each district make up just 1 percent of farmers but cultivate 12 percent of all land. The average farm in this study is 4.2 acres, which is divided into a little more than two plots.

**Table 5.1 Total farms and area farmed in India in 2007**

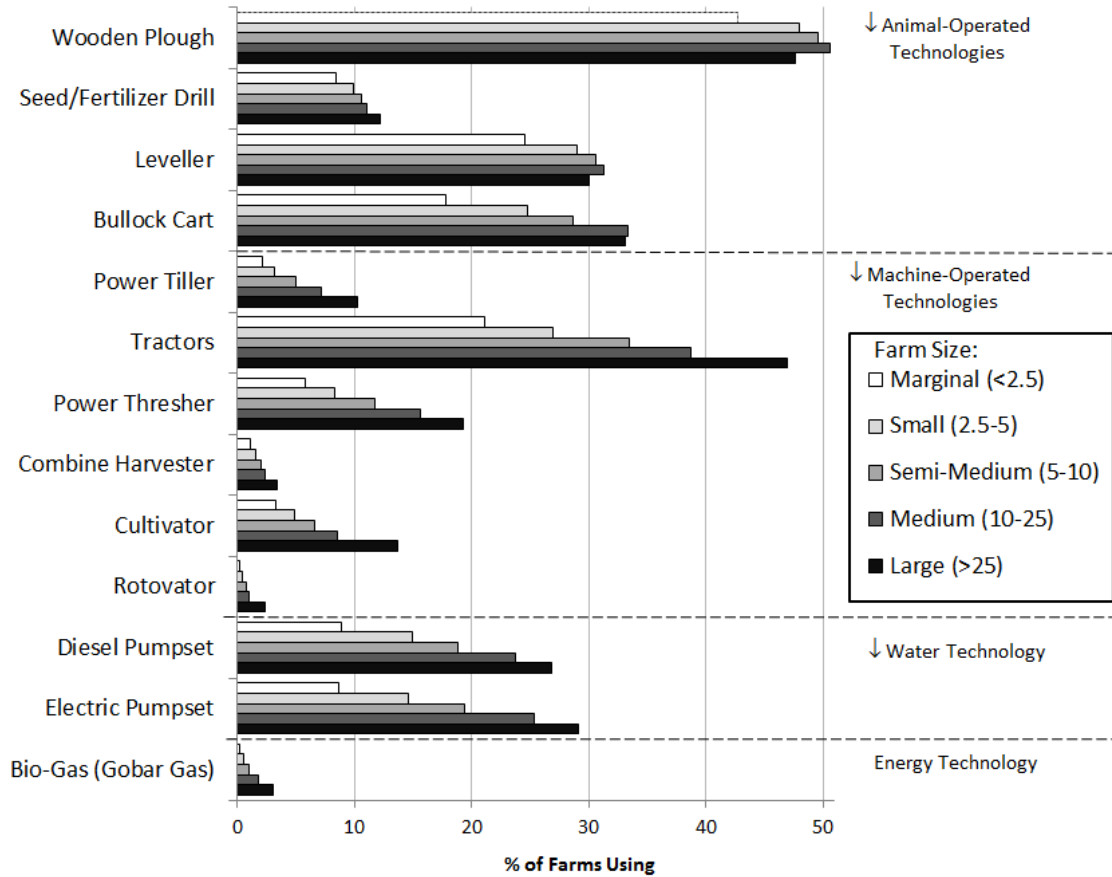
Size	Average number of farms per district	% of total	Average acres farmed per district	% of total	Average farm size	Average plot size	Plots per farm
Marginal (below 2.5)	123 (139)	0.64	128 (130)	0.21	1.21 (0.30)	0.86 (0.41)	1.67 (0.92)
Small (2.5 - 5)	36 (33)	0.19	126 (118)	0.20	3.45 (0.24)	1.78 (0.94)	2.75 (2.22)
Semi-Medium (5 - 10)	21 (22)	0.11	144 (150)	0.23	6.57 (0.49)	2.75 (1.79)	3.88 (3.54)
Medium (10 - 25)	10 (14)	0.05	147 (207)	0.24	13.44 (1.47)	4.60 (3.48)	5.14 (4.57)
Large (25 and above)	2 (6)	0.01	74 (256)	0.12	34.78 (24.97)	10.09 (11.01)	6.42 (7.60)
All	192 (169)		619 (628)		4.16 (3.90)	2.29 (2.46)	2.33 (1.45)

Source: Author.

Notes: Standard deviations in parentheses. Column 2 and 4 are measured in thousands. N = 371.

Figure 5.2 shows how technology use varies by farm size and technology type. As might be expected, marginal farms make the least use of all technologies, compared with the rest of the farm size groups. For animal-operated implements, the difference in technology use by farm size is less clear for farmers not in the marginal group, that is, cultivating more than 2.5 acres. This may be the first evidence of a farm size threshold effect for animal-powered technology, where small to large farmers use roughly the same amount and marginal farmers lag. Machine-operated implements have a much clearer distinction between all farm size groups. Nearly half of all large farms use tractors, compared with about a third of semi-medium farms and a quarter of all small farms. This suggests a potentially much higher farm size threshold for machines, which likely incur higher fixed costs and a greater scale on which to operate.

**Figure 5.2 Differences in percentage of farms using specific technologies across farm size**



Source: Author.

Overall, animal-drawn wooden plows are found in 45 percent of farms, whereas levelers and bullock carts are used in about a quarter of farms. Machine-powered implements are generally used less. Diesel and electric pump sets are found in 12–13 percent of farms. As discussed in more detail below, water-related technologies adopted as a result of NREGA’s heavy emphasis on water infrastructure can have a significant impact on labor use, which in turn can alter labor-saving technology adoption decisions. Both water- and energy-related technologies show a pattern of adoption across farm size similar to that of machine-operated technology.

## 6. RESULTS

Table 6.1 compares the initial OLS, difference-in-differences, and panel fixed effects results. As discussed earlier, OLS results are biased because they do not account for endogeneity between technology adoption and participation in the NREGA program. Columns 3 and 4 contain results from the difference-in-differences specification. The first uses overall percentages of farms using labor-saving technology in each district in 2004 and 2007 ( $n = 848$ ) as the dependent variable. This approach yields an increase of 10.3 percentage points in overall technology adoption in NREGA districts. This means that a district whose initial labor-saving technology adoption rate was 71.9 percent—the 2004 average rate—will now see 82.2 percent of its farms adopt labor-saving technology when NREGA is implemented. In column 4, the observations are disaggregated by the five farm size categories and clustered at the district level, yielding an increase of 7.27 percentage points in farms adopting technology. When district fixed effects are included, in columns 5 and 6, the impact on aggregate district-year data increases to 14.9 percentage points and, with farm size controls, decreases to nearly 10. These are all much higher than the naive OLS estimates in columns 1 and 2.

**Table 6.1 OLS, DD and panel regression results**

	OLS		DD		Panel FE	
	(1)	(2)	(3)	(4)	(5)	(6)
NREGA	0.0664*** (0.0189)	0.0673*** (0.0177)	0.00462 (0.0296)	0.0171 (0.0262)		
Post			-0.122*** (0.0229)	-0.0744*** (0.0200)	-0.125*** (0.0289)	-0.0585** (0.0255)
NREGA*Post			0.103*** (0.0383)	0.0727** (0.0345)	0.149*** (0.0534)	0.0997** (0.0422)
Constant	0.645*** (0.0113)	0.618*** (0.0118)	0.718*** (0.0183)	0.665*** (0.0159)	0.714*** (0.0168)	0.657*** (0.0145)
Farm Size Dummies	No	Yes	No	Yes	No	Yes
Observations	848	3,661	848	3,661	848	3,661
R-squared	0.012	0.038	0.048	0.048	0.749	0.597

Source: Author.

Notes: OLS = ordinary least squares; DD = difference-in-differences; FE = fixed effects. Robust standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Table (6.2) shows separate estimates of equation (5) for each farm size category. The marginal and small farmer groups see higher impacts on labor-saving technology adoption, with increases of 18.5 and 12.2 percentage points, respectively. As farm sizes get larger, the effect becomes smaller and less significant. For the largest size group, however, the number of observations drops dramatically, because there are not many farms in the sample larger than 25 acres.

**Table 6.2 Panel fixed effect regressions by farm size**

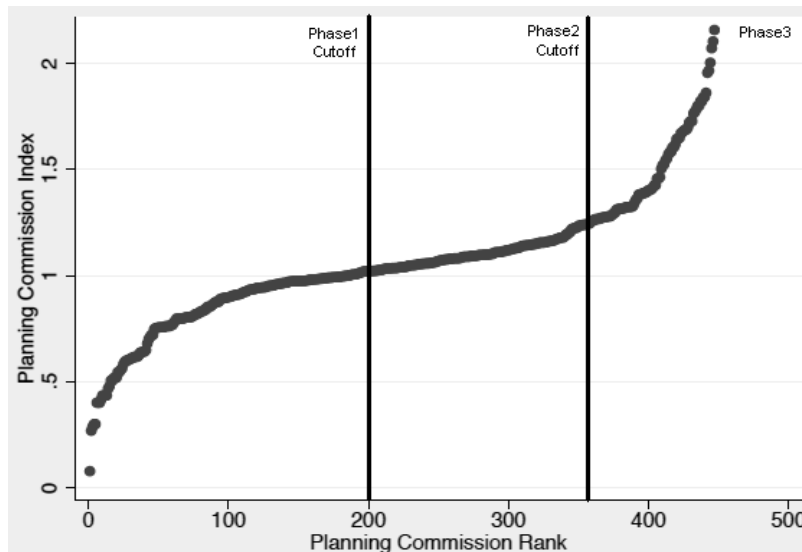
	Marginal (1)	Small (2)	Semi-Medium (3)	Medium (4)	Large (5)	Overall (6)
Post	-0.178*** (0.0315)	-0.0818** (0.0359)	-0.0104 (0.0395)	0.0282 (0.0603)	-0.00267 (0.148)	-0.125*** (0.0289)
NREGA*Post	0.185*** (0.0584)	0.122* (0.0643)	0.111 (0.0700)	0.0414 (0.0972)	-0.138 (0.204)	0.149*** (0.0534)
Constant	0.715*** (0.0185)	0.731*** (0.0212)	0.715*** (0.0235)	0.720*** (0.0370)	0.807*** (0.0988)	0.714*** (0.0168)
Observations	828	798	777	703	555	848
R-squared	0.760	0.759	0.758	0.766	0.848	0.749

Source: Author.

Notes: Robust standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \*p<0.1.

Before conducting the RD estimations, let us look at two graphs that can help further describe the data. The first (Figure 6.1) shows how the Planning Commission's Backwardness Index varies with the ranking assigned to each district in the country. This figure reveals that many of the most developed districts were not ranked in the index. This does not matter as much when comparing Phase I districts with those in Phases II and III versus comparing Phase I and II districts with those in Phase III, as would be required with National Sample Survey data. Clearly, districts ranked 400 and higher no longer become good comparisons for any group.

**Figure 6.1 Distribution of index over ranks with official phase cutoffs for implementation**



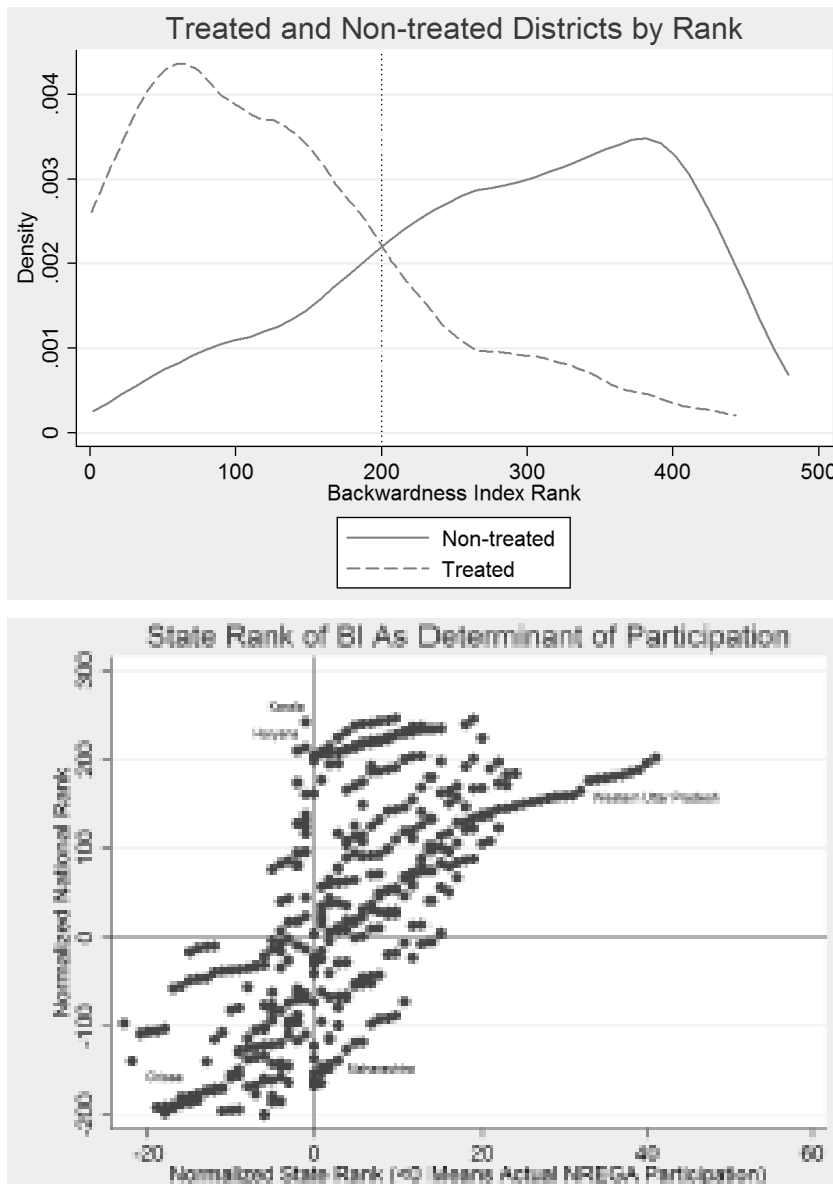
Source: Zimmerman (2012).

The top panel of Figure 6.2 shows density functions of the Backwardness Index rank for both NREGA and non-NREGA districts. While most of the districts fall within the first 200 if they are in NREGA and above 200 if not, there are tails for each group that overlap. This is due to imperfect assignment of NREGA according to rank. Kerala, for example, does not have any districts poor enough to rank below 200. When the poorest Kerala district receives NREGA, then districts just below the cutoff move to above the cutoff, for example, Gujarati districts that are more likely to fall under 200.



Zimmerman (2012) discussed a potential alternative NREGA assignment algorithm that would give each state at least one NREGA district by first considering the district's rank within the state. The bottom half of the graph in Figure 6.8 shows how being nationally ranked in the first 200 corresponds to one's normalized state rank, where the last district in each state to receive NREGA is assigned a state rank of -1. State ranks of zero and above indicate no NREGA treatment. Quadrants 2 and 4 show compatibility with a district's national and state ranks. Quadrant 1 shows the districts that received NREGA treatment even though their rank was above the official cutoff. Similarly, quadrant 3 shows that the districts who didn't receive NREGA treatment even though they ranked below 200 are even more numerous. It may be helpful to think of the long tail in quadrant 2 as districts in highly developed Kerala, almost all of which were above zero, and the group of districts closest to the origin as those in Uttar Pradesh, a state with more than 20 districts receiving NREGA treatment.

**Figure 6.2 Fuzzy regression discontinuity design**

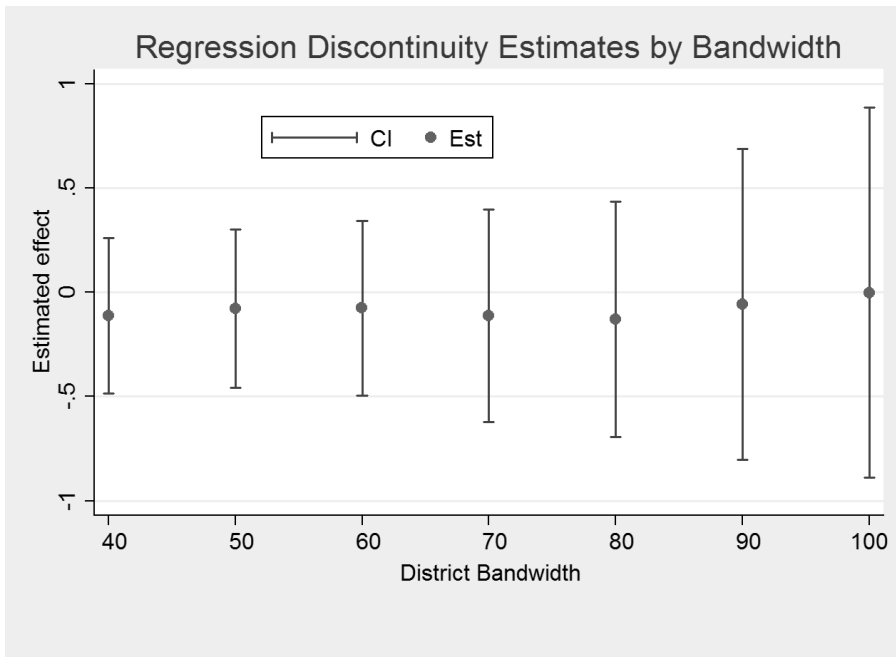


Source: Author.

Notes: Top panel: density of running variable (BI rank) for groups that received treatment versus those who did not. Some districts above the 200 district cutoff implemented NREGA. Bottom panel: the normalized national rank against state rank normalized to actual participation. Most states implemented NREGA in at least one district even if all ranks were above official cutoff (quadrant II).

Figure 6.3 shows estimates of equation (6) for bandwidths of between 40 and 90 districts. The selection of bandwidth is what determines the districts used in the analysis. Larger bandwidths include more districts away from the threshold, thus affecting the calculated probabilities of treatment; that is, more districts are included in the calculation of the local linear regression but with triangle kernel weights that drop more gradually as observations get farther away from the cutoff. Smaller bandwidths mean fewer districts are included in the calculation of the estimated local linear regression with weights dropping more rapidly for points away from the cutoff.

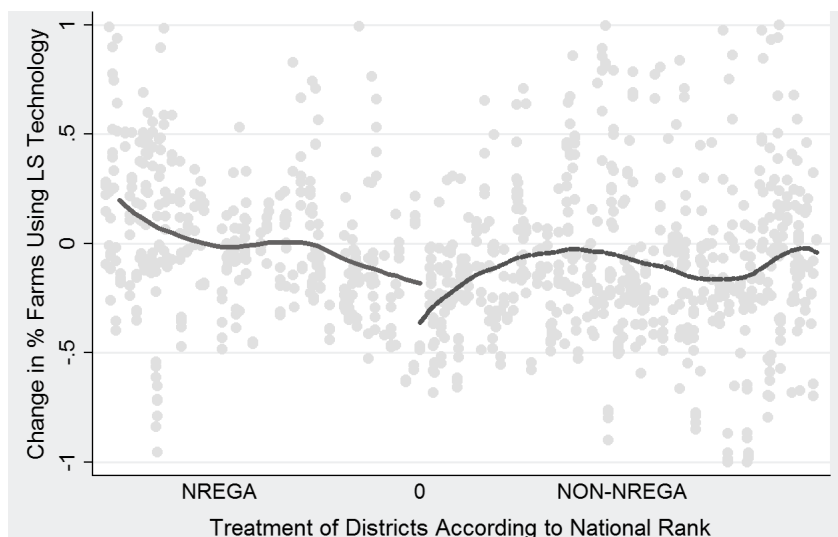
**Figure 6.3 Overall estimates of NREGA effect on labor-saving technology using regression discontinuity design at bandwidths between 40–100 with confidence intervals**



Source: Author.

Since, as discussed above, a fuzzy RD design will require a larger bandwidth than would a sharp design in order to calculate probabilities of treatment at the threshold, regressions at bandwidths of 30 and lower are not able to generate predictions of treatment at the cutoff. The first bandwidth where the power is high enough is 40 districts, and the top end is 90 districts in accordance with the highly curved tails observed in Figure 6.3. Figure 6.4 graphically depicts two fitted curves on either side of the normalized NREGA cutoff using a 40-district bandwidth and a dependent variable of the change in percentage of farms adopting labor-saving technology from 2004 to 2007. This picture stays consistent when considering the jump at the cutoff in 2007 alone.

**Figure 6.4 Jump in labor-saving technology**



Source: Author.

Note: Curves fit to the left and right of the normalized NREGA cutoff. Y-axis measures change in percent of farms adopting labor-saving technology between 2004 and 2007.

Table 6.3 shows estimates of the jump at the cutoff for these different bandwidths. In this specification, 2004 adoption is treated as a right-hand-side variable in order to not restrict the coefficient on it to 1. The numerator for each of these bandwidths is the jump in the outcome variable at the cutoff, which is what would be the final estimate if the RD design was sharp. However, in the fuzzy design, the jump in the probability of treatment at the cutoff is used as the denominator of the final Wald estimate. Here, the results are negative and the “treatment” is switched to not receiving NREGA. So with the tightest possible bandwidth that allows for estimation of the treatment effect, one sees an 11-percentage-point decrease in labor-saving technologies adopted by non-NREGA districts compared with NREGA districts. As in the case of the panel fixed effects estimates, the variation increases when more of the sample is included. However, here it renders the results insignificant at each bandwidth.

**Table 6.3 Overall regression discontinuity results with treatment effect equal to jump in adoption rates over jump in treatment probability**

	<u>Jump in Adoption Rates</u>		<u>Jump in Treatment Probability</u>		<u>Treatment Effect</u>	
	Coef.	SE	Coef.	SE	Coef.	SE
40 districts	-6.8	13.8	60.8	32.9	-11.2	19.0
50 districts	-4.2	12.3	55.1	32.0	-7.7	19.4
60 districts	-3.4	11.4	46.3	32.4	-7.4	21.4
70 districts	-3.5	10.0	31.3	30.6	-11.3	26.0
80 districts	-3.3	9.1	25.5	28.3	-12.9	28.9
90 districts	-1.1	8.5	20.2	27.0	-5.6	38.1
100 districts	0.0	8.0	17.6	26.0	-0.1	45.3

Source: Author.

Notes: Bandwidths are measured in number of districts to the left and right of cutoff. Jump in the adoption rates estimates changes in percent of farms adopting labor-saving technologies at NREGA cutoff, where NREGA district are on the left of threshold and non-NREGA districts on the right. Jump in the treatment probability represents the change in probability of treatment of NREGA cutoff. The treatment effect is the quotient of the two, or local Wald estimate, measured in percentage points.

To combat this high variance problem, the analysis considers technologies on an individual basis to compute estimates of jumps. Binswanger and Ruttan (1978) and Pingali, Bigot, and Binswanger (1987) shed light on which technologies to consider and what result to expect from NREGA. Both discussed how labor-saving agricultural technologies relate to mechanization and farming intensity, but the former was specific to India. In fact, Binswanger and Ruttan (1978) warned that much of his discussion was specific to the agroeconomic conditions in Punjab.

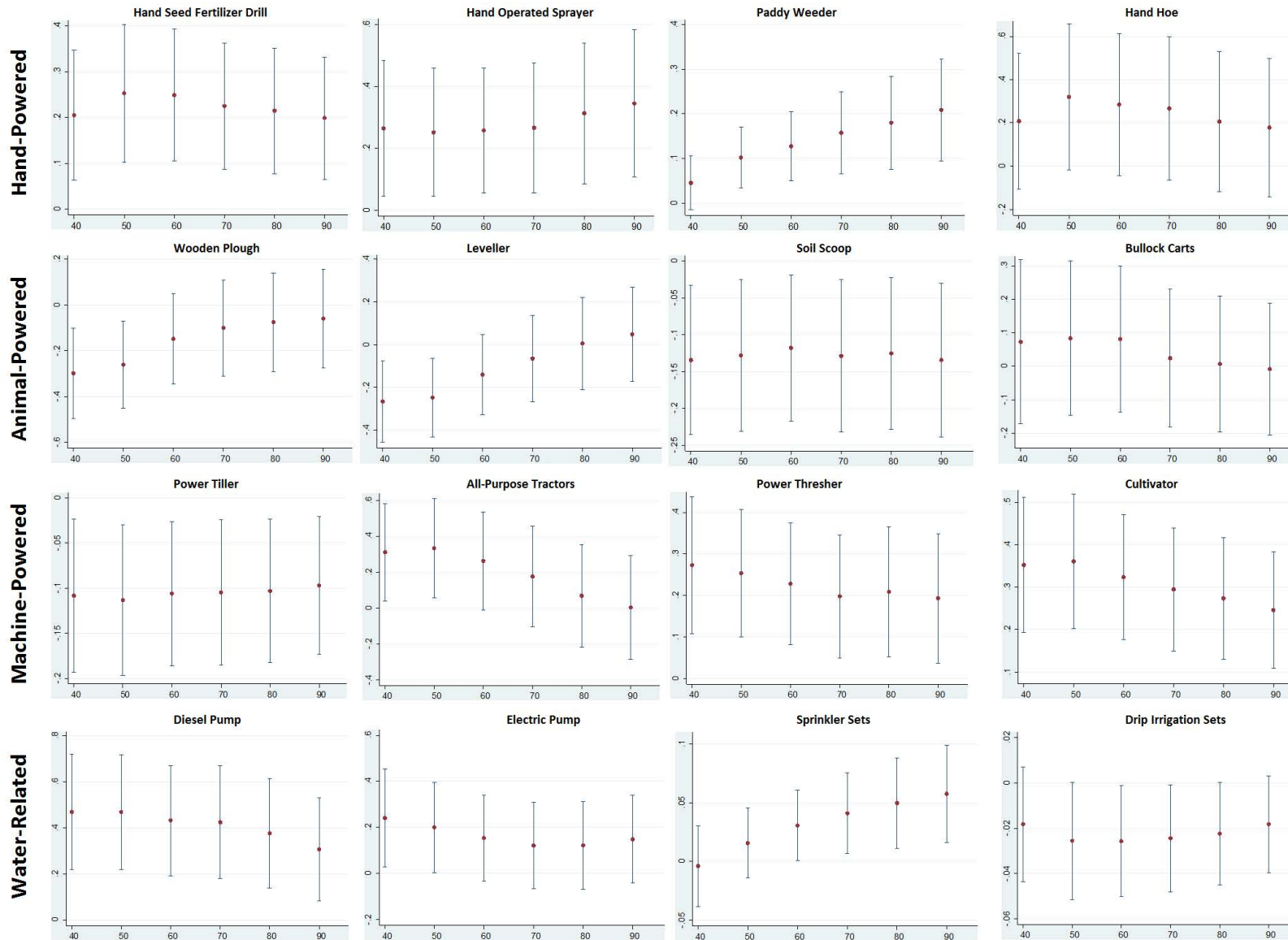
The adoption of tractors and tractor-related machinery, including seeders and levelers, is perfectly labor-saving when the substitution view of Binswanger and Ruttan (1978) holds. That is, the only reason for adoption of this equipment is factor prices or factor scarcity. On the other extreme, this sort of mechanization would not be labor-displacing and would be considered net contributing in that it achieves intermediate products and yields that are unattainable by labor, such as deeper tillage or higher precision. Net contributing technologies could also increase the speed of operations, allowing for a greater range of potential cropping patterns. This latter sort of technology might even lead to additional labor usage for any farm operations not performed by machines, such as land preparation, planting, weeding, chemical spraying, fertilization, harvesting (if not already mechanized), threshing, marketing, and transportation.

Tractor-powered machines used for tillage, irrigation, threshing, sowing, and transport are most likely (Pingali, Bigot, and Binswanger 1987). However, the order of mechanization for land-scarce areas would be first to intensify water use by upgrading to diesel and electric pump sets, which are labor-saving holding land amounts fixed but could be labor-intensive if farmers expand into marginal lands because of better irrigation. Mechanical mills and tillage and transport equipment follow, but threshing is generally not mechanized where wages are low and harvested volumes are small. Weeding, interculture, and harvesting continue to be done by hand in land-scarce economies where nonagricultural demand for labor is low. One would expect NREGA to increase mechanization for these technologies on the margin.

A consideration of individual technologies must rely on 2007 data only since the 2004 data are less specific on the exact technologies being used. Figure 6.5 shows estimates versus bandwidths for selected technologies. The top row shows hand-operated implements, which one would expect to be more abundant on farms not affected by NREGA, where labor is more abundant. For hand-operated seed drills, chemical sprayers, and weeders, positive jumps are observed. Changes in hand hoes for land preparation are mostly nonzero for NREGA districts, as they are for wheel hoes and blade hoes (not shown) at various bandwidths.

Most of the key labor-saving animal-powered implements are adopted less in those districts not receiving NREGA. The first three graphs of the second row of Figure 6.5 show that wooden plows, traditional levelers, and soil scooping all were adopted more in NREGA districts. Bullock carts, however, do not show a significant impact. This may be because bullocks had already been counted as those that pull plows and levelers. Machine-powered implements show an interesting pattern. Almost all seem to be associated with non-NREGA districts, indicating complementarity with labor abundance. This may be a sign of increases on the intensive and extensive margin by farms and a net contributor view of labor-saving technology. Finally, it is interesting to note that more pump sets and increased sprinkler irrigation are used in non-NREGA districts. This could be due to the public investment in irrigation and water infrastructure in NREGA villages as well as the abundance of labor needed to intensify farming as a result of improved irrigation.

Figure 6.5 Estimates of jumps in technology use at NREGA cutoff by technology type



Source: Author.

## 7. CONCLUSION

NREGA is one of the largest development programs ever implemented and, consequently, its direct and indirect effects are likely to be large and far-reaching. In addition to providing rural laborers with an important source of income and building much-needed infrastructure in and around the poorest villages in the country, it can also alter short- and long-run equilibria in other areas of the rural economy, such as labor, technology, and agricultural output. This study theoretically models how incentives for agricultural technology adoption change due to NREGA's impact on the opportunity cost of agricultural labor and tests these implications empirically.

Using data collected during the phased rollout of the program, the analyses uses an RD design to estimate changes in labor-saving technology adoption of around 20 percentage points, confirming the threshold model predictions of a reduction in the cutoff farm size associated with basic labor-saving technology adoption when agricultural wages increase. Results show that this reduction occurs within the marginal and small farmer groups, and while it is possible that participation in NREGA by small farming households creates income and credit effects that directly boost use of agricultural technology, the labor-saving nature of adoption suggests that at least some of NREGA's impact on technology is channeled through the increased opportunity cost of unskilled labor.

This research brings the analysis of NREGA closer to determining its long-run impacts on the poor. There is evidence so far that the rural poor's incomes are increasing, village infrastructure is improving, and agricultural wages are going up. This study finds that labor- and water-saving technology are also being affected. What remains to be seen is what the net impact of these changes will be on poor farmers and laborers in the long run. Continued reverberations between labor, technology, and NREGA in the rural economy can result in a win-win situation for farm owners and laborers to the extent that the technologies adopted increase farm productivity and that newly created NREGA infrastructure increases market access. However, with poor-quality infrastructure and low levels of education and skill development, laborers could be worse off in a post-NREGA era. A focus on education, skill development, and quality infrastructure may augment the chances that the former scenario plays out.

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