The Impact of India's Rural Employment Guarantee on Demand for Labor-Saving Technology

Job Market Paper

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October 2013

Abstract

While India's GDP has grown at substantial rates for most of the past decade, leading to the emergence of a strong middle class, around 645 million Indians remain poor and over half of these severely poor, according to a 2010 multidimensional poverty index. Many of these make up the over 700 million Indians who remain dependent on rural wage work. The Mahatma Gandhi National Rural Employment Guarantee Act (NREGA) addresses this by offering paid public works employment to the poorest rural laborers, boosting rural incomes and infrastructure. In this research, I show that the program also can lead to the unintended consequence of premature labor-saving technology adoption. I develop a theoretical model showing that NREGA's provision of public works employment to unskilled rural labor could raise rural wages to the point where farm owners substitute technology for labor in the short run. Whether this happens or not is an empirical question. The progressive rollout of the program allows me to use panel and regression discontinuity methods that yield an estimated 10 percentage point increase in labor-saving technology due to the program. These results show a decrease in the threshold cutoff farm size for technology adoption that occurs within the smallest farm groups, where animal-powered implements are the first to replace labor previously done by hand.

Though NREGA benefits poor laborers and hampers farm owners in the short run, the long-run impacts may reverse this scenario. I argue that whether owners and workers benefit from the program in the long run will depend on productivity increases due to adoption, the quality of NREGA's public works, and the degree of permanence of adopted technologies. Future data will allow testing of long-run impacts to complement short-run results presented here.

JEL: H53, J20, O12, O33, Q12

Keywords: Technology Adoption, Labor Markets, Poverty, NREGA, India

1 Introduction

Landless agricultural laborers and marginal farmers constitute much of India's poor. As the 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 solve these problems by providing guaranteed public works employment to unskilled rural laborers at minimum wages.

Passed into law in 2005, NREGA guarantees any household up to 100 days per year of rural public works employment at state-level minimum wages. These works must be within 5 kilometers of the household's residence and assigned within 15 days of application. Remuneration depends on state-specific minimum wages, usually about $2 per day. The law is modeled after the Maharashtra Employment Guarantee Scheme (EGS) of the 1970-80's 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. To date, NREGA projects have focused primarily on water and road infrastructure, and half of all workers have been women–far surpassing the 25% quota set by the government at the outset of the program.

While much of the existing research on NREGA focuses on transparency and accountability of implementation, the enormous scale on which the program operates also has lead to a growing number of studies on unintended outcomes. For example, 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% unskilled agricultural wage increases across India (Imbert and Papp, 2013; Berg et al., 2012; Azam, 2012). Shah (2012) phrases a similar finding as a 30% reduction in wage sensitivity to farm production shocks for every one standard deviation increase in NREGA infrastructure. These wage increases are biased towards women, and this has led to higher overall rural labor force participation rates (Azam, 2012; Zimmermann, 2012). However, due to the recency of these gender gap findings, earlier suggestions of private sector crowding out due to NREGA have been challenged (Zimmermann, 2012). Nevertheless, all studies found the program to be well-targeted to poor laborers indicating significant jumps in poor household incomes.

This research moves the program analysis one step further by focusing on how these effects of NREGA on rural labor markets in turn alter technology adoption decisions by farm owners. Since farmers depend on the unskilled labor targeted by NREGA, a change in workers' wages, incomes, and migration patterns is likely to alter the input price ratio and decrease the technology adoption threshold. During informal focus groups held in eastern Uttar Pradesh in late 2011, I found that farm owners expressed unease about labor "not being there," meaning workers were not willing to work at the same wages they used to receive. In other words, wages appeared to be going up but any change in the size of the labor force was ambiguous. Many farm owners cited the much bigger relative increase in wages for women due to NREGA as a possible reason. Laborers, on the other hand, recognized they could get higher wages for the same amount of labor for some farm tasks, though others were no longer as easy to find. This suggests labor-saving technology adoption that favors some production tasks over others.

I incorporate both farm owner and unskilled labor views into a theoretical model of a workfare program's impact on labor-saving technology adoption. I specify peak- and lean-season characterizations of labor combined with a threshold technology adoption model that explicitly depends on agricultural wages. The resulting hypothesis is an increase in labor-saving technology adoption in NREGA districts. Using panel fixed effects and regression discontinuity designs, I find a 10 percentage point increase in the percentage of farms per district using labor-saving technology, with small and marginal farmers seeing the biggest increases. This indicates that NREGA's impact on agricultural wages has made technology relatively less expensive to the farmer and lowered the technology adoption threshold.

In addition to heterogeneous impacts by farm size, technology-specific regressions reveal that animal-powered implements appear to be replacing their hand-operated counterparts due to the program. Non-NREGA districts use hand-powered implements significantly more than NREGA districts, while the reverse is true for animal-drawn ploughs and levelers. Machine-powered technology, however, does not follow this pattern. Binswanger's "net contribution" view of certain technologies requires that a farm to have a certain minimum amount of labor in order to make profitable technologies that increase operations on the intensive or extensive margins (Binswanger 1978). Since most farms that fall within NREGA districts are losing labor and are small in terms of acreage, they may be moving further away from net contributing machine-powered technology and replacing labor first with animal-powered implements.

These results bring the analysis of NREGA one step further in determining its full impact within poor villages. The short run view is becoming clear: unskilled laborers, especially women, now receive rural wages both through public works and agriculture that are inching closer to official minimum wages. Indeed, Imbert and Papp (2013) argue that the poorest sixty percent of NREGA villagers–regardless of whether they themselves perform public works–receive roughly half of their welfare gain from agricultural wage increases alone. Farm owners, on the other hand, suffer in the short run and must adapt to their new economic environment by increasing the use of labor-saving technology.

In the long run, the complete impact of NREGA is still uncertain. On the one hand, if farmers are locked into their new technologies, then, when NREGA ends, unskilled farm jobs would no longer be available for the poorest workers, and they would find themselves worse off than before, especially if short-run income gains do not lead to a higher sustainable income path for the poor. On the other extreme, however, farm productivity may increase due to new technology, and NREGA infrastructure may develop to the point where farm owners can increase operations on the intensive and extensive margins, creating more jobs in the long run at higher wages.

Where NREGA will fall between these two extremes depends on at least three factors: 1) how much new technology will lead to farm expansion, 2) whether or not technology can easily be disadopted if equilibrium wages fall back to previous levels after NREGA, and 3) the type and quality of infrastructure developed by NREGA. On the second point, it is clear that custom-hire technology markets are especially popular for the smallest farmers in India, suggesting technology can be adopted on per-use basis as a result of NREGA and perhaps just as easily disadopted in the future. Regarding infrastructure development, rural connectivity and water-related projects make up 20% and 50% of NREGA projects, respectively. Both can boost farm production and offset both initial decreases in labor use due to the public works program and any subsequent decreases in labor use due to adoption of labor-saving technology. This study finds that water-related technologies are adopted significantly less in NREGA villages, demonstrating that water-related infrastructure may be making an impact on farm owners' input and technology choices. Future data on long-run labor use, wages, and technology adoption patterns will give much better insight into where NREGA villages eventually end up on this long-run spectrum.

The rest of this paper is structured as follows. Section 2 discusses the motivation and structure of NREGA and reviews literature related to the employment guarantee's impact on labor and technology markets. Section 3 develops a peak- and lean-season theoretical model that ties together increases in agricultural wages due to an employment guarantee with the adoption of labor-saving technology. Section 4 discusses the main panel and regression discontinuity methods used in the empirical approach, and Sections 5 and 6 provide discussion of the data and results, respectively. Section 7 concludes.

2 Background

In this section I first describe in more detail the motivation behind NREGA and its specific poverty-related goals. I then look 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. In Section 2.3, I discuss 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. Finally, I review the literature on how both the quantity and quality of village infrastructure investment affect labor and technology markets in helping determine long run outcomes.

2.1 NREGA

NREGA offers local wage-employment for public village development projects, guaranteeing every unskilled laborer 100 days of public works employment in their own village at a wage of at least Rs. 100 per day. This employment guarantee is not the first program of such a scale to take place. Conditional cash transfers (CCT), such as *Bolsa Família* and *Oportunidades*, as well as the Public Distribution System (PDS) 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. 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 requirement is school attendance, health clinic visits and nutritional support, a NREGA unskilled laborer must work on infrastructure development projects in their 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, Fafchamps, and Sadoulet 1991; Binswanger, Khandker, and Rosenzweig 1993; Fan, Hazell, and Thorat 2000; Narayana, Parikh, and Srinivasan 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. Drèze studied closely a government response to the severe drought in Maharashtra in 1970-73 known as the Employment Guarantee Scheme (EGS) (Dreze, 1990). He 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 cites 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" (p 17). And "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" (p 25). NREGA guarantees work to laborers who either lose their seasonal work in bad years or who 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 their own minimum amount of 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 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 the minimum wage payment 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, then, have a financial incentive implement NREGA and keep unemployment low in their villages.[1]

Finally, NREGA tried to incorporate from the Maharashtra EGS methods 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

[1] Wage seekers have the right to unemployment allowance from their local government in case NREGA employment is not provided within 15 days of submitting the application or from the date when NREGA work is sought.

themselves into the treatment, ensuring both the objectives of getting aid to those who are of highest risk of starvation and also avoiding elite capture.[2] 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.

2.2 Employment Guarantees and Agricultural Labor Markets

Though the theoretical literature on guaranteed employment and rural labor impacts are 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) find both a 5.5% increase in agricultural wages and crowding out of private sector employment. Berg et al. (2012) find roughly 3% increases 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% increase in female agricultural wages but only 1% for men.

All these studies used difference-in-differences estimation to find increases in agricultural wages of between 3-5%, while highlighting private sector impacts only during the dry season and gender-neutrality in impact distribution. Shah (2012) estimated a 6.5% increase in agricultural wages and additionally found that a one standard deviation increase in infrastructure development due to NREGA leads to a 30% reduction in wage sensitivity to production shocks. Zimmermann (2012) uses a regression discontinuity design and finds 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 do not develop theoretical models explaining how an employment guarantee should impact agricultural wages. Of those that do, Imbert and Papp (2013) draw heavily from earlier models showing the distributional effects of price changes on consumption goods by simply replacing the latter with labor markets. Zimmermann (2012) uses a very simple minimum

[2] Narayana, Parikh, and Srinivasan (1988) also discusses the topic of elite capture in the EGS and show that a program carried out efficiently, targeted effectively and financed properly is effective in alleviating poverty in India.

wage model and adds 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, Parikh, and Srinivasan (1988) stylized the Indian agricultural labor market by separating demand into peak and lean season. They then show how the EGS changes the market. This is shown in Figure 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 agricultural purposes. With the lean season labor demand curve, D_L, workers are only hired 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, it is inconclusive and depends on the magnitude of the shift in D_L whether or not agricultural wages increase. As long as L_T is less than L, i.e., 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.[3]

Osmani (1990) sees the agricultural wage determination process in India differently. He argues that farm workers collectively determine the equilibrium wage via repeated wage-setting games. The equilibrium wage becomes higher than the competitive wage due this "implicit cooperation." Workers ask for a wage above their opportunity cost and employ a "trigger strategy" that penalizes any worker who undercuts theme 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 at least be 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 (see Figure 2). This pushes up Osmani's equilibrium wage interval, which has c as its lower

[3]Even in the case where $w_P \leqslant w_N$, there should still be no affect on the peak agricultural labor market because both EGS and NREGA intend employment to only be offered during the lean agricultural season.

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 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 cites several factors that determine this interval and where exactly the equilibrium wage falls that include a worker's time discount factor and subjective probability of employment.

Basu (2011) develops a theoretical model of an employment guarantee that predicts impacts on output and labor markets. His model features 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 casual agricultural laborer during the peak season. He finds that 1) an increase in the public works wage results in a decrease in agricultural labor and 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 highly 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 assumes that workers cannot perform lean season agricultural work and public work at the same time.

Nevertheless, Basu does use his model to consider the impact of an EGS on agricultural employment and wages under different labor market specifications. For example, he shows that a landlord who is confronted with a minimum wage, $\bar{w}$, but simply wants 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, both of whom are represented by separate labor unions that can contest agricultural wages against the other group in a non-cooperative way. This is an extension of Osmani's implicit cooperation model. But again it is highly stylized: the existence of labor unions was more specific to the Kerala case at that time and not generalizable to the Indian context as a whole, especially poorer states. The results of the game theoretic extension results in upward pressure on agricultural wages. When there exists an additional permanent versus casual labor distinction, Basu builds on previous tied-labor literature to argue that an EGS wage that offers more than the lean-season casual labor wage would induce more permanent labor contracts, which would be beneficial to those who get the contract. This is because the EGS increases the cost to the landlord of hiring casual workers during the lean and peak seasons as needed and makes the purchasing of permanent worker contracts across an entire year more attractive. This would mean less employment for some of the poorest workers in the economy who are casual but better employment in terms of permanent contracts for others.

2.3 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) reviews technology adoption models that discuss the role of land tenure, farm size, uncertainty, and information. The authors caution against a trend in the literature at the time of "nonexistence of government policies in most adoption models" (p 288), which can affect relative input and output prices and, therefore, technology choices. Besley and Case (1993) critique time-series adoption models for being too broad in nature and less useful for determining individual adoption practices. But they also note that most cross-section empirical studies ignore adoption dynamics and focus only on the correlation between farmer characteristics and final adoption. The authors suggest a more a balanced approach and highlight dynamic optimization studies that model state dependence between periods and test adoption practices using panel data. They conclude that most of the previous studies do not account well for factors such as information and access to credit. Finally, Foster and Rosenzweig (2010) highlight 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 do not explicitly address the role of labor availability in technology adoption. Hicks and Johnson (1979) and Harriss (1972) examine 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) demonstrates 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 that is characterized by large quantities of land and small amounts of labor. Labor supply constraints are shown 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 end of the land-labor ratio spectrum, which is more characteristic of countries like India.

It is clear that the role of labor availability was a topic in much earlier studies of technology adoption. But the discussion of determinants has moved away from this towards previously lesser known issues, such as finance, information and risk. Empirical work on technology adoption has thus shifted towards changes in these explanatory variables and consequently found interesting results with many policy implications. This research fills a gap in recent literature by re-examining and re-modeling the role of labor availability in technology adoption. I begin 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. I develop the threshold model to explicitly account for changes in labor markets and restrict the outcome to labor-saving technologies in order to capture the theoretical effects of NREGA.

2.4 Infrastructure Investment

Finally, I review some of the literature on infrastructure investment and discuss how this 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) look at links between investment decisions of governments, financial institutions and farmers in 85 districts across 17 states in India. They measure 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 agro-climatic variables, the authors use fixed effects to identify the impacts of roads, primary schools and electrification on agricultural output growth, which were shown to have significant positive effects of 7, 8 and 2 percent, respectively. Private investment, such as on tractors, fertilizers, pumps, and animal purchases by farmers show mixed effects. The use of tractors by farmers increased 6% due to canal irrigation, whereas roads improved agricultural output 6.7%. These were both significant in affecting both agricultural input use and output levels, as well as encouraging private investment. Fan, Hazell, and Thorat (2000) show that rural roads and agricultural research have the highest per Rupee impact on poverty and productivity growth in India, with only modest impacts of irrigation, soil and water conservation, health, and rural and community development.

de Janvry, Fafchamps, and Sadoulet (1991) focus on the transaction cost wedge of rural villages and show pathways through which physical rural development can benefit the poor. These authors address the seeming paradox that peasant farm households do not respond to price changes in a way that is consistent with traditional economic theory and argue that it is the lack of infrastructure that keeps transaction costs high prevents 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, Parikh, and Srinivasan (1988) released a study around the same time as Dreze's post-Maharashtra EGS analysis that looks at the potential of rural works programs (RWP) 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 show, 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," they claim that rural works programs "also improve rural infrastructure, thereby increasing productivity of land.

3 Model

This section brings labor and technology markets together to determine the theoretical short-run effects of NREGA. First, the effect of NREGA on agricultural wages is examined and, then, the subsequent impact on technology adoption. The model shows how even rural works program that is intended for lean-season implementation only can raise wages in both the lean and peak production periods. A farm owner who wants to keep production constant must shift to the technology market to do so when labor costs rise. This shift is expressed as a reduction in the minimum farm size needed to cross the "threshold" to labor-saving technology adoption.

3.1 Agricultural Wages

In this section, I develop a theoretical model of labor market effects due to an employment guarantee that incorporates both farm owner and laborer optimization problems over lean and peak agricultural seasons.

As in Frisvold (1994), the farmer first produces a lean-season standing crop in the first period

$$q_L = q_L(L_L, K_L, \theta_L) \tag{1}$$

where L_L is lean season labor, K_L is a vector of lean season material inputs and θ_L contains exogenous variables, such as land quality and soil type. The goal of the farmer is to maximize the standing crop during the lean season since final production of the crop is considered be Leontief in lean- and peak-season production.

Given the lean season agricultural labor demand schedule, the laborer chooses between consumption, c_L, and leisure, l_L, with an income constraint, y, that is a function of agricultural labor input, L_L^S, lean season wages, w_L, migration labor, L_M, migration wages, w_M,[4] the price of consumption, p_L, the opportunity cost of leisure, w, and exogenous income, h_L. The laborer's maximization problem, then, can be written as

$$\max_{c_L, l_L} \quad U(c_L, l_L) \tag{2}$$

subject to

$$p_L c_L + w l_L \leq y = w_L L_L^S + w_M L_M + h_L, \, T = l_L + L_L^S + L_M,$$

where T is the total time endowment.

Solving equation (2) yields optimal schedules for c_L^*, L_L^{S*}, and L_M^* that depend on the functional form of the utility function, the price of consumption, agricultural wages, and the value of w. Additional assumptions on how L_L^S and L_M enter the utility function can help determine the relationships of these quantities relative to one another.

In the peak season, the farmer now maximizes profit by choosing peak season labor, L_P, as well as additional harvest inputs, K_P, to achieve final output, q_P. Final output, thus, is a function of lean season output and peak season inputs so that $q_P = q_P(q_L(L_L, K_L, \theta_L), L_P, K_P)$. The farmer's maximization problem becomes

$$\max_{L_L, L_P, K_L, K_P} \quad \pi = p\, q_P(q_L(L_L, K_L, \theta_L), L_P, K_P) - w_L L_L - w_P L_P - r_L K_L - r_P K_P \tag{3}$$

where p is the output price, r_L captures prices of capital used in the first period and r_P contains prices for capital used in the second period.

Laborers maximize the following utility function in the peak season:

$$\max_{c_P, l_P} \quad U(c_P, l_P) \tag{4}$$

subject to

[4] The migration wage is net of the transaction costs of performing the migration.

$$p_P c_P + w_P l_P \leq y = w_P L_P^S + h_P,\ T = l_P + L_P^S$$

where c_P refers to peak period consumption and the opportunity cost of leisure equals w_P. Migration outside the village during peak production period is assumed to not be undertaken in the peak period.

I now look at the impact of the introduction of NREGA on these optimal producer and laborer decisions. Consider the offer of NREGA employment, L_N, at wage, w_N, during the lean season only. Equation (2) now becomes:

$$\max_{c_L, l_L} \quad U(c_L, l_L) \tag{5}$$

subject to

$$p_L c_L + w l_L \leq y = w_L L_L^S + w_N L_N + w_M L_M + h,\ T = l_L + L_L^S + L_N + L_M$$

Compared to the optimal labor inputs from equation (2), L_L^{S*} and L_N^* in the post-NREGA era will now depend additionally on the NREGA wage.

The difference between L_L^{S*} in both the pre- and post-NREGA eras is the effect of the program on agricultural labor input, if any. Additional effects may occur on peak season labor supplied only if y in the constraint of equation 4 contains income carried over from the lean season. Farm owners will now maximize equation 3 accounting for a potential decrease in L_L and, subsequently, q_L, according to equation 1.

The difference between the pre- and post-NREGA time constraints for the laborer is the addition variable, L_N. For a fixed value of time, T, a positive value of L_N means that at least one of the remaining variables in $T = l_L + L_L^S + L_M + L_N$ must decrease but does imply that any one variable increases or decreases for sure. For example, an increase in L_N may result in a decrease in L_L^S or L_M. Or, it could lead to an increase in $l_L$and decrease in both L_L^S and L_M.

To the extent that there is sufficient excess labor supply during the lean season to satisfy both the 100 days of NREGA work and the demand for farm labor, one would expect to see the repercussions reflected by a decrease in L_M. This is the theoretical implication of Narayana, Parikh, and Srinivasan (1988). To the extent that "implicit cooperation" (Osmani, 1990) is occurring in NREGA villages, the uptick in opportunity income may result in an increase in the equilibrium wage and decrease in labor input, depending on the factors described in the previous section. If there is not sufficient excess labor supply in the lean season or if the post-NREGA labor allocation leaves L_L^{S*} lower than before, farm owners will be quantity constrained in labor and the equilibrium lean season agricultural wage will rise. The empirical evidence generally supports this latter hypothesis.

In summary, the effect of NREGA on agricultural markets can be summed up by the following equation:

$$w_L = w_L(L_L^S(NREGA)) \tag{6}$$

where we know that

$$\frac{\partial w_L}{\partial L_L^S} < 0 \tag{7}$$

but are unsure of the sign and magnitude of

$$\frac{\partial L_L^S}{\partial NREGA}. \tag{8}$$

3.2 Technology Adoption

If the emerging empirical evidence on higher wages and decreased employment is true, this will lead the farm owner to reconsider previous technology adoption decisions. I first try to capture the intuition behind changes in agricultural labor and technology markets graphically using Figure (3).

Before NREGA the profit-maximizing farmer was able to use capital and labor to the point where the marginal value products of these two inputs were equal. Point A captures this initial equilibrium of agricultural labor and wages. This wage is equal to wages in all other rural labor sectors in the village, including public works (Point B) and the total labor market. That is, $w^A = w^P = w^*$. Due to the payment of minimum wages for rural laborers via NREGA, the public works wage is now subject to a price floor at w^N. Whereas L^P workers would have accepted

w^P(point B), now L^N laborers earn w^N (point C) and more public works projects are undertaken in the village, provided this amount of labor is less than the 100 day cap per person set by the program.[5] This causes a shift inward and results in two possible scenarios. If NREGA work can cover a worker's entire income for the year and if the worker is indifferent between public works and agricultural labor, then the agricultural labor supply curve shifts to $S_A^{''}$ and results in a new agricultural equilibrium at Point D. The worker must be paid at least w^N to work on the farm. However, NREGA work alone is not likely to satisfy a rural laborer's demand for work. Thus, the new agricultural supply curve, $S_A^{'}$, is likely to instead shift in between the two extremes of S_A and $S_A^{''}$, resulting in Point E. This corresponds to an aggregate labor supply of $L^{'}$ and equilibrium wage of $w^{'}$ (Point F), which lies between the new agricultural wage, $w^{A'}$, and the NREGA wage, w^N, as a result of the shift out of the total rural labor demand curve from D to D'.

The quantity $L^A - \bar{L}$ is known as the notional excess demand for agricultural labor, defined as the difference between "the amount...that people would want to buy...if they ignored any constraints on the quantity of other goods they were able to buy" (DeLong, 2010) and the amount they are actually able to buy given the constraints. Here the constrained amount is. As Muellbauer and Portes (1978) point out, "an agent who is rationed as a buyer or seller on one market and cannot transact his notional excess demand there will in general alter his behavior on other markets" (p. 789). This is depicted at the bottom of Figure (3) where the demand for labor-saving agricultural technology shifts out until the marginal value products of labor and technology are equal at the new agricultural labor allocation. Thus, farm owners cannot satisfy their excess notional demand for agricultural labor, and this affects both agricultural wages and their activity on the technology market.

Mathematically, induced technology adoption can be modeled as follows. Consider first the case of a farm owner maximizing profit and relying on unskilled labor in the pre-NREGA era

[5] There are very few cases where any worker in a NREGA village completed 100 days of public works throughout the year. There are many potential explanations for this, including corruption or the fact that the program is intended only to be stopgap employment for severe work shortages, which, due to the relative nature of this intention, are likely not to cover more than 100 days in the year.

(corresponding to Point A in Figure 3). The farmer's problem is to

$$\max_{K,L} \qquad \pi^{1u} = pf(K,L) - w^A L - rK, \tag{9}$$

where wages are known and u denotes unconstrained. Equation (9) is a generalization of equation (3) above. Equation (9) results in an unconstrained optimal labor demand curve. After the implementation of NREGA, there is a shift in the agricultural labor supply curve from $S_A \to S'_A$ and the farmer is quantity-constrained in the short-run. Wages rise to a new equilibrium that sets the increased marginal opportunity cost to the laborer of working on the farm to the farm owner's derived demand schedule.

The farmer may now reconsider his options in the production process and seek other markets in which to transact his notional excess demand. Before the implementation of NREGA he preferred his unconstrained profits using the existing technology, π^{1u}, to the unconstrained profits from any new technology, π^{2u}. Now that his profit maximization under the old technology has been constrained, he receives only $\pi^{1c} < \pi^{1u}$, where c denotes the constrained profits. He must compare these constrained profits without the technology to the constrained profits with the technology:

$$\pi^{2c} = pf(K,aL) - w^{A'} L - rK - F, \tag{10}$$

where F is the fixed cost of the new technology and $a > 1$ incorporates its labor-saving nature. The change in the optimal amount of capital used in production, as well as whether the optimized profit level, π^{2c^*}, is greater than π^{1c^*}, will depend on the relative magnitudes of F, a and $w^{A'}$. I now incorporate these profit functions into a threshold model of adoption to obtain empirically testable results.

3.2.1 Threshold Model

Sunding and Zilberman (2001) discuss a method to model the technology adoption threshold using heterogeneity of farm size as the determining factor. Though technically this is a diffusion model, it can also describe individual farmer adoption. Each farmer earns $\triangle\pi_t$ more profit from the new technology as compared to the traditional one for each time t. Adoption takes place only above a certain cutoff farm size, H_t^c, which depends on the farmer-specific levels of fixed costs, F_t, and the difference in profit, so that

$$H_t^c = F_t/\triangle\pi_t. \tag{11}$$

Diffusion of the new technology increases (i.e. the cutoff farm size decreases) either as fixed costs decrease or differences in profit increase (i.e., $\partial\triangle\pi_t/\partial t > 0$). The authors relate this change in profits to a change in the variable cost differential between use of the two technologies, presumably focusing on price of the technology. In the case of NREGA, however, this change can be due to increasing agricultural wages, which effectively make the traditional technology more expensive and closes the gap between profits over time.

I explicitly incorporate the wage effect into the threshold model by using the profit functions from Equations 9 and 10. I further specifying equation (11) as

$$H_t^c = F_t/[\pi^{2c}(p,Q,w^{A'},aL,r,K) - \pi^{1c}(p,Q,w^{A'},L,r,K)], \tag{12}$$

where

$$\frac{\partial\pi_1}{\partial w^A} < \frac{\partial\pi_0}{\partial w^A}$$

because the technology represented by $\pi_1(\cdot)$ is labor-saving and, thus, less impacted by agricultural wages. The fixed costs from Equation 10 are now captured only in the numerator of Equation 12. Differentiation of this equation with respect to time corresponds to the marginal diffusion of technology or the increase in farmer adoption at time t.

One benefit of this 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 many studies are done in the large farm context only. For a labor-saving technology such as a combine harvester, there may be an even tighter constraint on farm size simply because many machines cannot operate on plots whose dimensions are too small.

3.2.2 Risk

Risk may play a factor in the adoption decisions of farmers. As noted earlier, the nature of the custom-hire technology market makes adoption decisions less irreversible than in other adoption studies. Nevertheless, uncertainty in both the success of the technology and government policies that affect the future wages of laborers can be considered in the threshold model. Previous studies have looked at effects on technology adoption decisions by modeling uncertainty in final output prices (Sandmo, 1971) and information or learning (Conley and Udry, 2010). Sunding and Zilberman (2001) cite two applications of a dynamic adoption model with irreversibility and uncertainty–one in irrigation technology adoption, where the random variable captures changing water prices (Olmstead, 1998), and the other capturing uncertain environmental regulations in the case of free-stall dairy housing adoption (Thurow et al., 1997). In this part, I let wages be uncertain to the farm owner since farmers in India were fearful of an increase in agricultural wages due to NREGA but did not know for sure if it would be the case and do not consider the success of the technology to be risky for the reasons mentioned above.

Using an expected utility function of profits, Just and Zilberman (1988) model the adoption threshold by looking at what proportion of land a farmer will apply new technology. This can be simplified to a binary adoption decision, where the farmer makes his adoption decision based on the difference between profits with and without the technology, accounting for heterogeneous constraints on credit, land and fixed costs (e.g. information availability, setup costs).[6] The authors' model specifies the farmer's optimization problem as a choice of amount of land devoted to the new technology, $H_1 \in [0, H]$:

$$\max_{I=0,1;H_0,H_1 \geq 0} EU[p_H H + \pi_0 H_0 + I(\pi_1 H_1 - rk)], \tag{13}$$

where $H_0 + H_1 = H$ is the land constraint, the technologies are represented by the subscripts 0 for the use of traditional technology and 1 for the new technology, p_H is the value of a farmer's

[6]This is similar to the model in Qaim and de Janvry (2003).

land, I is the binary adoption indicator, r is the interest rate, and k is the fixed cost associated with adoption. The authors note that the fixed costs associated with adoption do not necessarily affect the decision to adopt but will affect the aggregate distributional impact.

I replace final profits in the model with those in Equations 9 and 10, so that

$$\max_{I=0,1;H_0,H_1\geq 0} EU[p_H H + [pf(K,L) - w^{A'}L - \bar{r}K]H_0 + I([pf(K,aL) - w^{A'}L - \bar{r}K]H_1 - rk)], \quad (14)$$

renaming the rental price of capital as $\bar{r}$ and moving all the fixed costs of adoption into k. Because the uncertainty is now in $w^{A'}$, the expectation of profits will be affected by the variance of future wages.

The optimal amount of land dedicated to the new technology by a risk-diversifying farmer will be one of the following: 1) $H_1 = 0$: no adoption, 2) $H_1 = H_1^c < H$: adopt up until credit constraint, 3) $H_1 = H$: adopt up until land constraint, or 4) $H_1 = H_1^r < H$: interior solution (i.e. no binding constraints). Where a farmer falls among these options due to the wage increase (or expected wage increase) is an empirical question that will be tested empirically in Section 5.

3.2.3 Long Run

Because of how recent the NREGA intervention is, I cannot test long run impacts on farm owners and rural laborers. However, at least two theoretical scenarios are possible.

The first possibility is that, if the farm owner adopts the labor-saving technology, the long run demand for agricultural labor may shift in. Sunding and Zilberman (2001) describe F as embodying not only information and learning but also the physical upfront cost of new, indivisible equipment. But these technology choices may not be irreversible since agricultural capital markets in India are often characterized by custom-hiring, especially in small farm areas. This decreases the value of F for many farmers to include virtually only information and learning costs, which can be high for relatively new technologies but low those that have been available and used in a farmer's village but just not adopted yet for a particular farmer. Furthermore, many custom-hire technologies feature the owners of the capital themselves operating the technology, reducing further the amount of learning needed by adopters of custom-hire technologies. This all allows the technology adopter to more instantly make adoption decisions if further changes (or expected changes) in wages occur in the labor market. For example, if NREGA is no longer politically or financially able to continue, then the wages in the public works labor market may drop back to the unconstrained equilibrium amount and agricultural wages subsequently fall to their original level. The notional excess demand that was once shifted to an increase in capital markets may be shifted back to labor.

A second possibility is that, to the extent technology adoption leads to higher agricultural production in villages and to the extent NREGA is successful in building public infrastructure, demand curves for agricultural labor could shift out, since demand is a function of income, $D = D(Y)$. This is consistent with Binswanger's net contributor view of technology and is represented by point G in Figure 3, where the long run level of agricultural labor could range anywhere from $\underline{L}$ to L^A and beyond, depending on how far DA'' shifts away from DA in response to productivity increases. Meanwhile, both agricultural and total labor market wages approach and could even exceed the minimum wage, w^N. Agricultural wages that are higher in the long run under the new technology than in the original equilibrium would be consistent with the empirical findings of Minten and Barrett (2008).

4 Empirical Strategy

There are several approaches to estimating NREGA's effect on technology adoption. The progressive rollout of the program to most impoverished districts first and least impoverished districts last can cause concern for some empirical methods while leading more naturally to others. I first consider ordinary least squares (OLS) but argue that endogeneity will lead to biased results. Most NREGA studies have relied on difference-in-differences (DD) to identify causal impacts. I consider a general DD specification and a second that takes advantage of the panel nature of my data. In this subsection I discuss the validity of these estimates given the non-random assignment of NREGA across districts. Finally, I present a regression discontinuity design that takes advantage of the progressive rollout in evaluating changes in outcomes at the treatment discontinuity.

4.1 OLS

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

$$TA_{it} = \alpha + \beta * NREGA_{it} + \gamma * X_{it} + \varepsilon_{it},$$

where TA is the percentage of machines used in district i, $NREGA$ is a binary indicator of whether district i is a first phase NREGA village, and X is a vector of district-level controls. This 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 $E(\varepsilon_{it} \mid X_{it}) = 0$. This is not likely if districts that are more likely to adopt technology are also less likely to be poor (and, therefore, less likely to be a first-phase NREGA village). The econometric concern is reverse causality where NREGA technology levels in the district also determines whether the village receives NREGA treatment. There will also be strong correlation in outcomes within districts across years.

Thus, OLS estimates of the effect of NREGA participation on technology adoption ultimately will be biased but serve as an interesting comparison to better methods. To address this bias, I employ two econometric techniques: difference-in-differences (DD) and regression discontinuity design (RD), 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 to each other and the OLS approach.

4.2 Difference-in-Differences & Panel Fixed Effects

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

$$TA_{it} = \alpha + \beta NREGA_{it} \cdot post + \gamma post + \delta NREGA_{it} + \varepsilon_{it}, \tag{15}$$

where TA is the percent 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. Covering the number of farms using technology into a percent 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 (15) can be improved upon with panel data by including district fixed effects. The panel fixed effects equation is

$$TA_{it} = \beta NREGA_{it} \cdot post + \gamma_t + \delta_i + \varepsilon_{it}, \tag{16}$$

where now γ is a post-NREGA dummy representing the time fixed effect and δ is a district-level fixed effect for each district i. The main coefficient of interest in Equation 16 is β, which gives the treatment effect of NREGA on technology adoption net of time trends and time-invariant district characteristics.

I use this within estimator to counter 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. I do not explicitly test for parallel trends in this study, but, by using a regression discontinuity approach that does not require the common trends assumption, I can compare estimates between the two designs.

4.3 Regression Discontinuity Design

The regression discontinuity (RD) method does not require exogeneity of the treatment variable with the outcome. RD solves this identification challenge by assuming that villages around a treatment threshold are the same in all characteristics except for a certain exogenous factor which assigns the treatment to some and not to others. Lee and Lemieux (2009) argue 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."

The RD equation takes the form

$$TA_i = \alpha + \beta NREGA_i + \gamma rank_i + \delta rank_i^2 + \eta NREGA_i rank_i + \lambda NREGA_i rank_i^2 + \varepsilon_i, \tag{17}$$

where the dependent variable is the difference in adoption percentages in district *i* before and after the implementation of NREGA. $\alpha = TA_0$ is the initial difference over time in adoption rates for districts near the threshold that did not qualify for NREGA participation. $\beta = TA_1 - TA_0$ is the treatment effect of interest and *rank* is what determines the cutoffs for each phase based on the BI. I include the 2004 baseline technology adoption data 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 term in equation (17) allows 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 are appropriately weighted or the window of observations is restricted to the districts that make more natural treatment-control groups, due to similarity in characteristics before the program. In this study, I will weight observations away from the cutoff using a triangle kernel and also consider several windows around the theshold.

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 a RD specification be non-manipulable by the beneficiaries of the treatment. This can happen in the case of government healthcare for low-income individuals, for example, where employers may pay individuals slightly less in order to avoid private healthcare costs, thus contaminating the 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 (BI), which ranks the 447 poorest districts in India using wages, productivity and SC/ST[7] population percentage from the early and mid-1990s. The first 200 districts in the BI received NREGA funds in 2006, while next 130 began the program in almost two years later (see Figure 4). Because the government used measures from the 1990s to determine whether villages received NREGA treatment in 2006, this threshold variable does not appear 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.

I do use a fuzzy RD design, however, because, although districts theoretically become part of NREGA in a deterministic way solely dependent on their rank, i.e., $NREGA_i = f(rank_i)$ and they cannot manipulate the threshold variable, in practice 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 to their poorest districts, regardless of whether those districts were below the cutoff. I discuss this in more detail below using graphical depictions.

[7] Scheduled Caste/Scheduled Tribe

5 Data

The data for this study comes from the India Human Development Survey (IHDS) and the Ministry of Rural Development's Agricultural Census Input Survey (ACIS). Together, these datasets yield a district-level panel by farm size of the years 2004 and 2007. The circles in Figure 4 indicate when each dataset was collected. While these two panels allow for testing of the short-run technology adoption implications of the above model, both IHDS and ACIS will soon be releasing their next rounds of data allowing me to test long-run hypotheses, as well.

For short-run impacts of NREGA, a panel with these two endpoints is unique to previous studies on the topic. Previous studies mostly use 2008 National Sample Survey data as the end year, which restricts the analysis to comparisons of Phases 1&2 as the treatment and Phase3 as the control. This is problematic both because Phase3 districts are questionable controls for the poorest districts in the country (Phase1) and because pooling Phase1 and Phase2 districts together in 2008 ignores the fact that Phase1 districts had been receiving NREGA treatment twice as long as Phase2 districts (see Figure 4). Having 2004-2005 and 2007 data allows me to use treatment and control groups consisting of Phase1 and Phase2/3, respectively. In the regression discontinuity framework, this allows me to first trim the richest districts in India (Phase3) during analysis before estimating impacts at lower levels of development.

While the 2004-2005 IHDS data has been used extensively, particularly by sociologists interested in nutrition and intra-household decision making in India, the 2007 ACIS is lesser known. ACIS data is collected in three phases. First, the number of farm holdings in each district is recorded and tabulated by size, gender and social group. Then, random selection occurs within district at the block-level (or *tehsil*), which is an administrative unit at the sub-district level consisting of many villages. Each block then has 20% of its villages randomly selected (100% of villages are included for small states). Finally, the input survey itself is conducted for the final list of sample villages, ensuring that each village has at least four farms for each of the five farm size groups: marginal, small, semi-medium, medium, and large. Enumerators enact this final data collection phase after almost one year, thus placing the actual information collected at mid-2007, despite the official year of the survey being 2006-2007.

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

Figure 5 shows how technology use varies by farm size and technology type. As might be expected, marginal farms use all technologies the least compared to 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, i.e., cultivating over 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 behind. Machine-operated implements have a much clearer distinction between all farm size groups. Nearly half of all large farmers use tractors compared to about a third for semi-medium farmers 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.

Overall, animal-drawn wooden ploughs are found in 45% of farms, whereas levelers and bullock carts are used in about a quarter of farms. The number of machine-powered implements are generally used less. Diesel and electric pumpsets are found in 12-13% 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 2 compares 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 participating in the NREGA program. Columns (3) and (4) contain results from two difference-in-differences specifications. The first uses overall percentages of farms using labor-saving technology in each district in 2004 and 2007 (N=848). This approach yields a 10.3 percentage point increase in overall technology adoption due to NREGA districts. This means that a district whose initial labor-saving technology adoption rate was 71.9%–the 2004 average rate–will now see 82.2% of its farms adopt labor-saving technology when NREGA is present. In column (4), the observations are disaggregated by the five farm size categories and clustered at the district level, yielding a 7.27 percentage point increase in farms adopting technology. When district fixed effects are included, the impact on aggregate district-year data increases to nearly 15 percentage points (column 5) and with farm controls decreases to roughly 10. These are all much higher than the naive OLS estimates in columns (1) and (2).

Equation (16) is estimated separately for each farm size category in Table (3). The marginal and small farmer groups see higher impacts on labor-saving technology adoption of 18.5 and 12.2 percentage point increases, respectively. As farm sizes get larger, the effect becomes smaller and less significant. The latter may be due partly to smaller sample sizes for bigger farms. For the largest size group, the number of observations drops dramatically, as there are not many farms over 10 hectares.

Before conducting the RD estimations, I look at two graphs that can help describe the data. The first (Figure 6) shows the how the Planning Commission's Backwardness Index (BI) 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 BI. Thus, these will not be available as controls. This matters less when comparing Phase1 districts to those in Phase 2/3 as opposed to the contrary. For this analysis, they probably do not make good controls anyway if the pattern for the first 447 districts is any indication.

The top panel of Figure 7 shows density functions of BI 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 nonperfect 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) discusses a potential alternate NREGA assignment algorithm that gives each state at least one NREGA district by first considering the district's rank within state. Here, I show how being nationally ranked in the first 200 (bottom half of graph) corresponds to one's normalized state rank, where the last district in each state to receive NREGA is assigned a state rank of minus one. State ranks of 0 and above indicate no NREGA treatment. Quadrants II and IV show compatibility with a district's national and state ranks. Quadrant I shows the districts that received NREGA treatment even though their rank was above the official cutoff. Similarly, quadrant III shows that the districts who didn't receive NREGA treatment even though the had rank below 200 are even more numerous. It may helpful to think of the long tail in quadrant II as districts in highly-developed Kerala, almost all of which were above zero, and the group of districts closest to the origin as Uttar Pradesh, a state with over 20 districts receiving NREGA treatment.

Figure 8 shows estimates of equation (17) for bandwidths 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, i.e., 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.

Since, as discussed above, a fuzzy RD design will require a larger bandwidth than a sharp design in order to calculate probabilities of treatment at the threshold, regressions at bandwidths of 30 and lower were not able to generate predictions of treatment at the cutoff. The first bandwidth where this is possible is 40 districts, and I stop at 90 districts in accordance with the highly curved tails observed in Figure 6. Figure 9 graphically depicts two fitted curves on either side of the normalized NREGA cutoff using a 40-district bandwidth.

Table 4 shows estimates of the jump at the cutoff for these different bandwidths. In this specification, I allowed 2004 adoption to be a right-hand side variable in order to not restrict the coefficient on it to one. 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 to 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.

To combat this high variance problem, I take technologies on an individual basis to compute estimates of jumps. In order to determine which technologies to consider and what result to expect from NREGA, I consult Binswanger (1978) and Pingali, Bigot and Binswanger (1987). Both discuss how labor-saving agricultural technologies relate to mechanization and farming intensity, but the former is specific to India. In fact, Binswanger warns that much of it is specific to the agroeconomic conditions in Punjab.

The adoption of tractors and tractor-related machinery, including seeders and levelers, are perfectly labor-saving when the substitution view of Binswanger (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 first intensify water use by upgrading to diesel and electric pumpsets, 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, 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.

To look at individual technologies, I must use 2007 data only since the 2004 data is less-specific on the exact technologies being used. Figure 10 shows estimates versus bandwidths for select 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 all observed. Changes in hand hoes for land preparation are mostly nonzero for NREGA districts, as they are for wheel hoes and blade hoes (not pictured) 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 show wooden ploughs, 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 ploughs 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 pumpsets and sprinkler irrigation are adopted as a result of NREGA. 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.

7 Conclusion

NREGA is one of the largest public programs ever undertaken in India and, consequently, its direct and indirect effects are likely to be large and far-reaching. In addition to providing rural landless laborers with income in slack agricultural production periods and building much-needed infrastructure in the poorest villages, it can also alter equilibria in other rural markets and change incentives for farm owners. This study theoretically models the effect of NREGA on labor-saving technology adoption through changes in agricultural wages.

Using the phased rollout of the program over several years, I conduct difference-in-differences and regression discontinuity estimates of changes in labor-saving technology adoption. I find an overall increase in adoption of around 10 percentage points for farm owners in districts that implement NREGA. The threshold model predicts a reduction in the cutoff farm size associated with adoption when agricultural wages increase, and I find that this reduction occurs within the marginal and small farmer groups. Due to relatively high degrees of labor market segmentation, especially in the poorest districts of India, I am able to test this second-level unintended consequence of the NREGA program.

This brings the analysis of NREGA in the literature closer to determining the long-run impacts of NREGA on the poor. As of now, there is evidence that the rural poor are getting richer, village infrastructure is improving, agricultural wages are increasing, and labor-saving technology is being adopted in NREGA districts. What remains to be seen is what the net impact of this will be on both poor farmers and poor laborers in the long run. The competing effects on agricultural labor demand will be the subject of future research on NREGA villages as these effects ripple through the rural economy.

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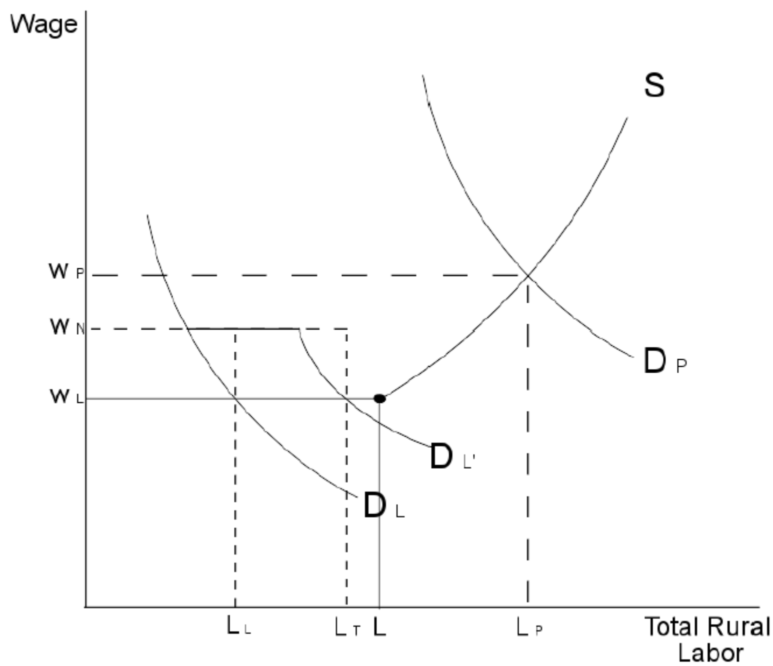

Figure 1: Agricultural and NREGA Labor Supply with Peak and Lean Season Demand (Narayana, Parikh, and Srinivasan, 1988)

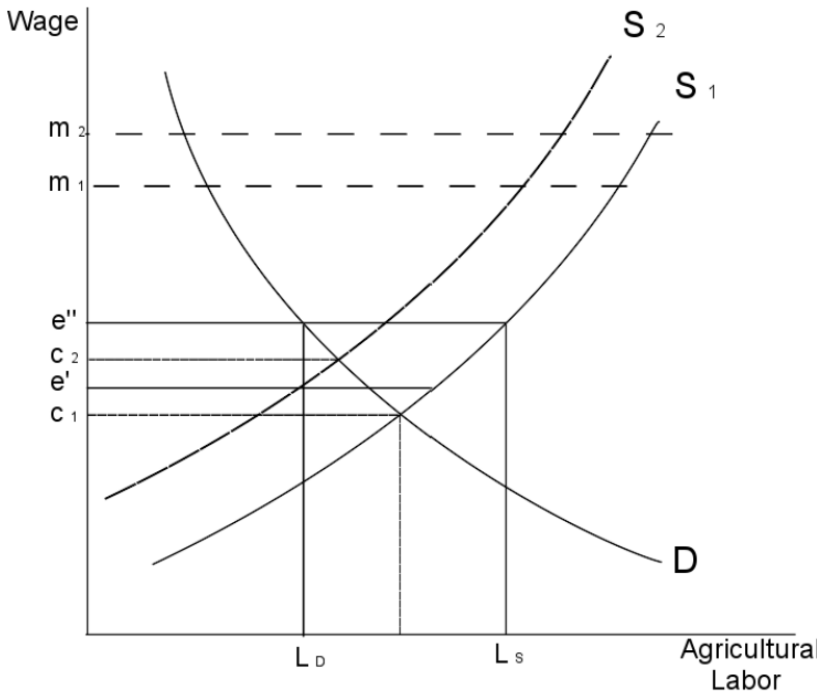

Figure 2: Implicit Cooperation Amongst Workers Leads to Equilibrium Wage Above Competitive Wage (Osmani, 1990)

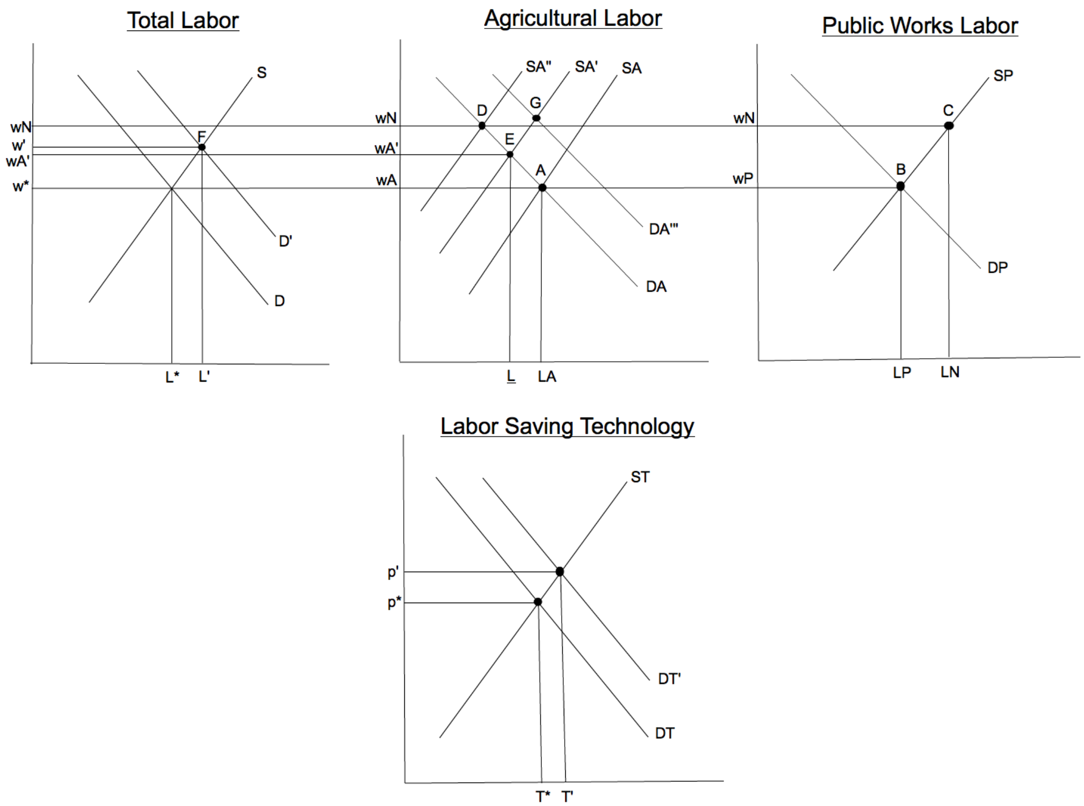

Figure 3: Short and Long Run Effects of NREGA on Rural Labor and Technology Markets

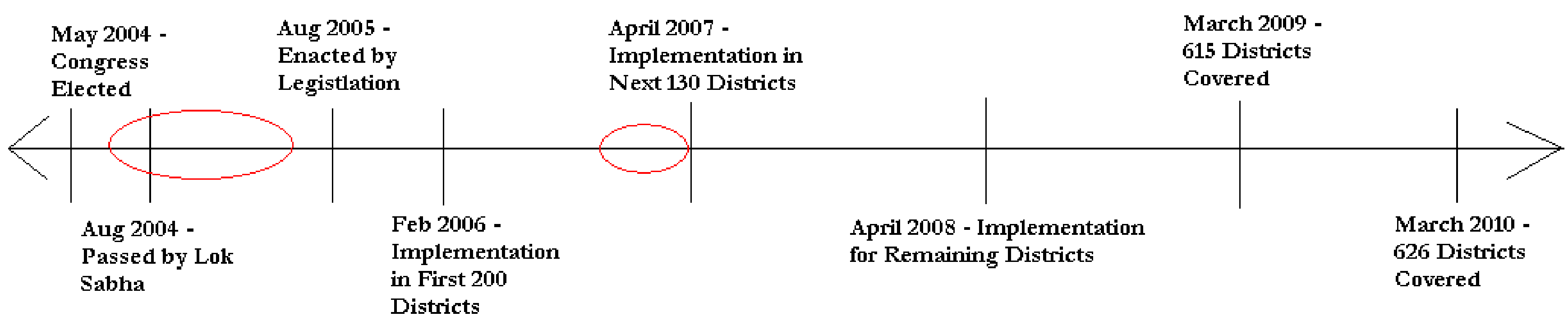

Figure 4: Evolution of NREGA. The Indian National Congress party was elected into power in May 2004 and passed NREGA into law in August 2004. The first data collection (circled) occurred just before enaction of legislation in August 2005. The first districts received NREGA public works projects in February 2006, and the second data collection occurred at the end of that phase before the next 130 districts received NREGA funds in April 2007. By March 2010, NREGA was implemented in all distics in India.

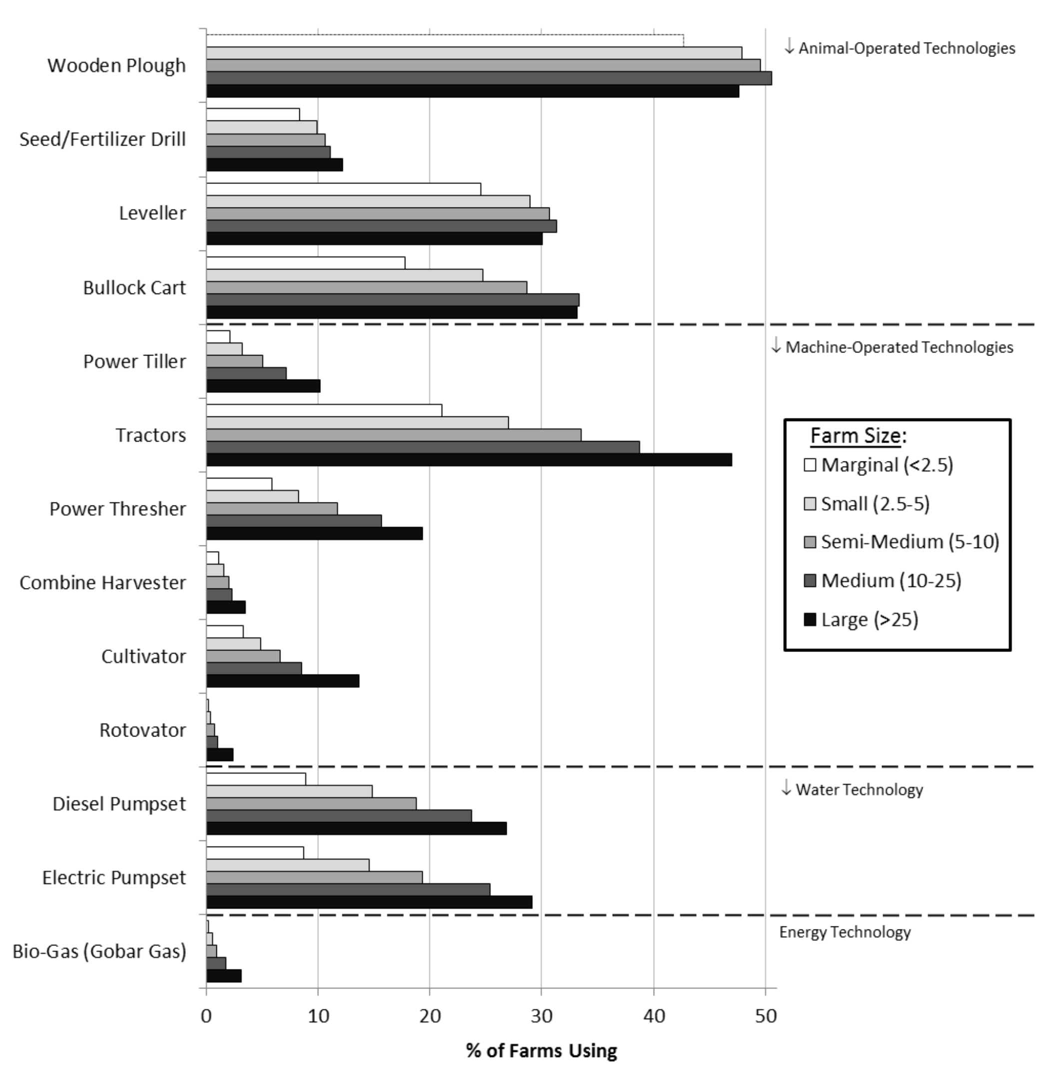

Figure 5: Differences in percentage of farms using specific technologies across farm size

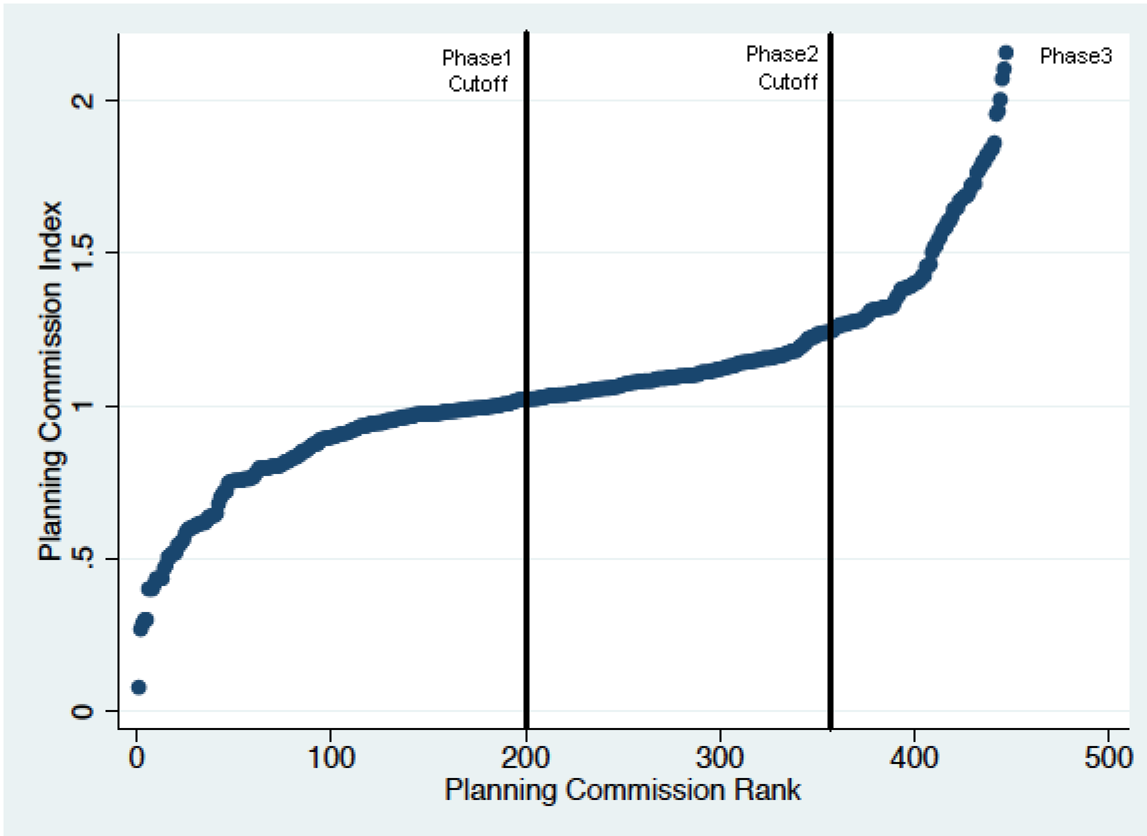

Figure 6: Distribution of Index over Ranks (Source: Zimmerman 2012) with Official Phase Cutoffs for Program Implementation

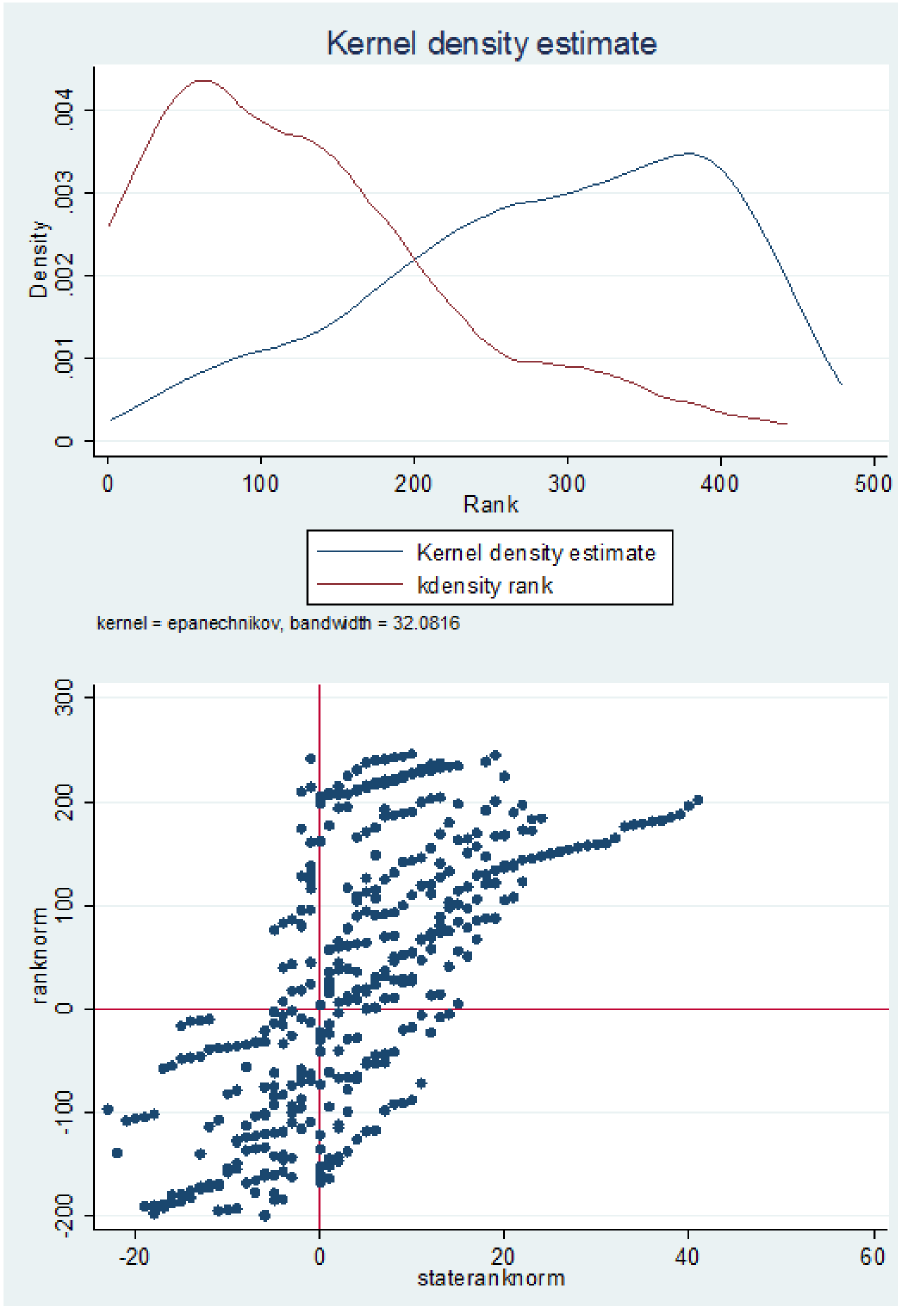

Figure 7: Fuzziness of RD Design. Top panel: density of actual NREGA rank for groups that received treatment versus those who did not. A rank of 200 or below is the official cutoff for NREGA participation. Bottom panel: the normalized rank of NREGA districts nationally (y-axis) versus within state (x-axis). Some states received at least one treatment district even if rank was above the official cutoff.

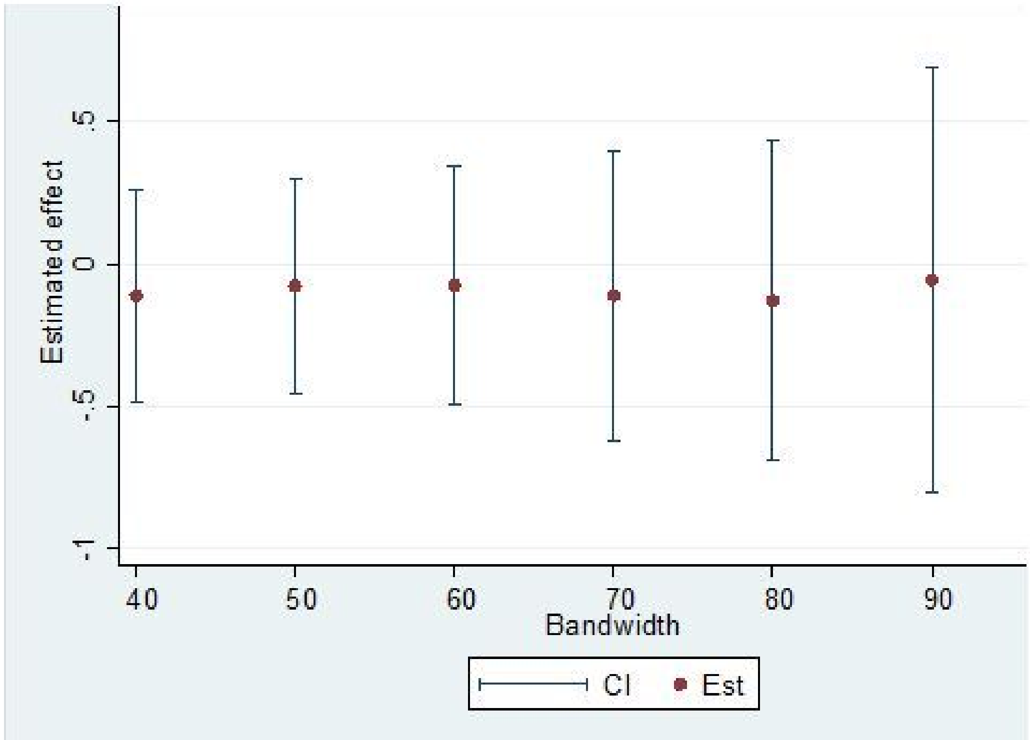

Figure 8: Overall estimates of NREGA effect on labor-saving technology using regression discontinuity design at bandwidths between 40-90 with confidence intervals

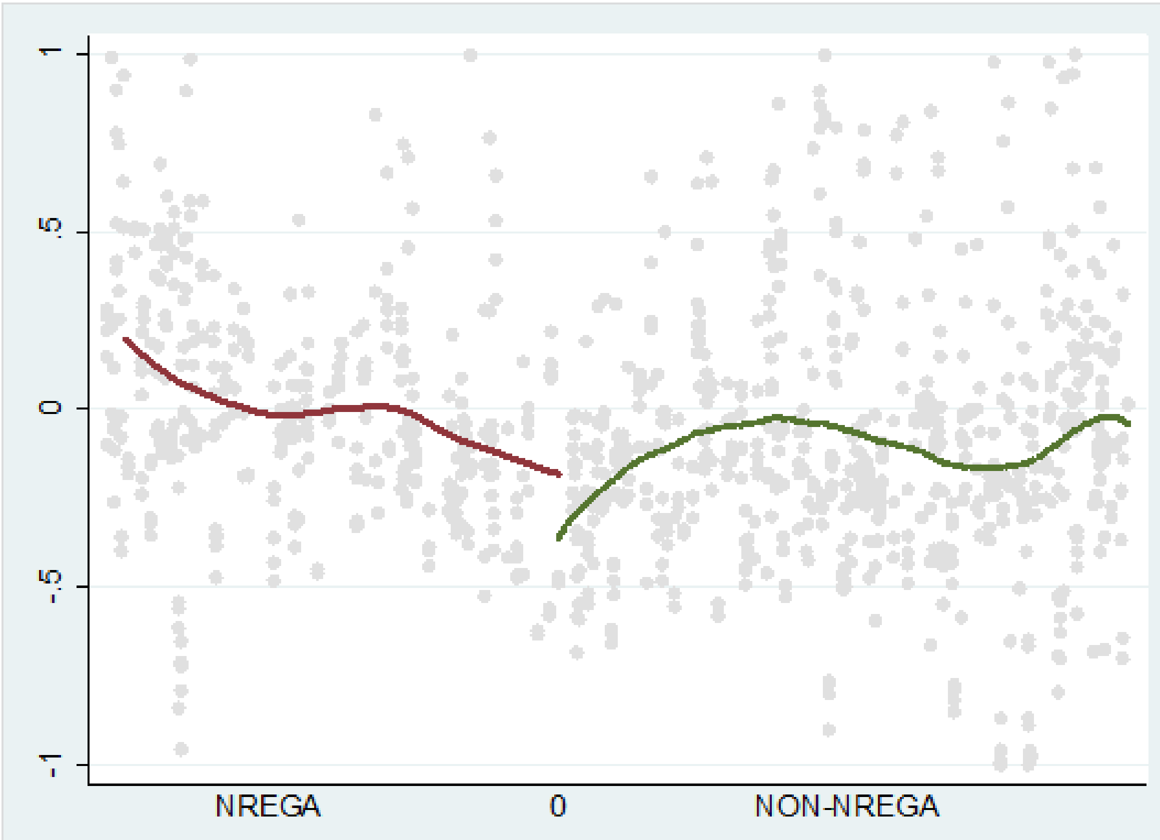

Figure 9: Curves fit to the left and right of the normalized NREGA cutoff. Y-axis measures change in percent of farms adopting labor-saving technology between 2004 and 2007 on the y-axis.

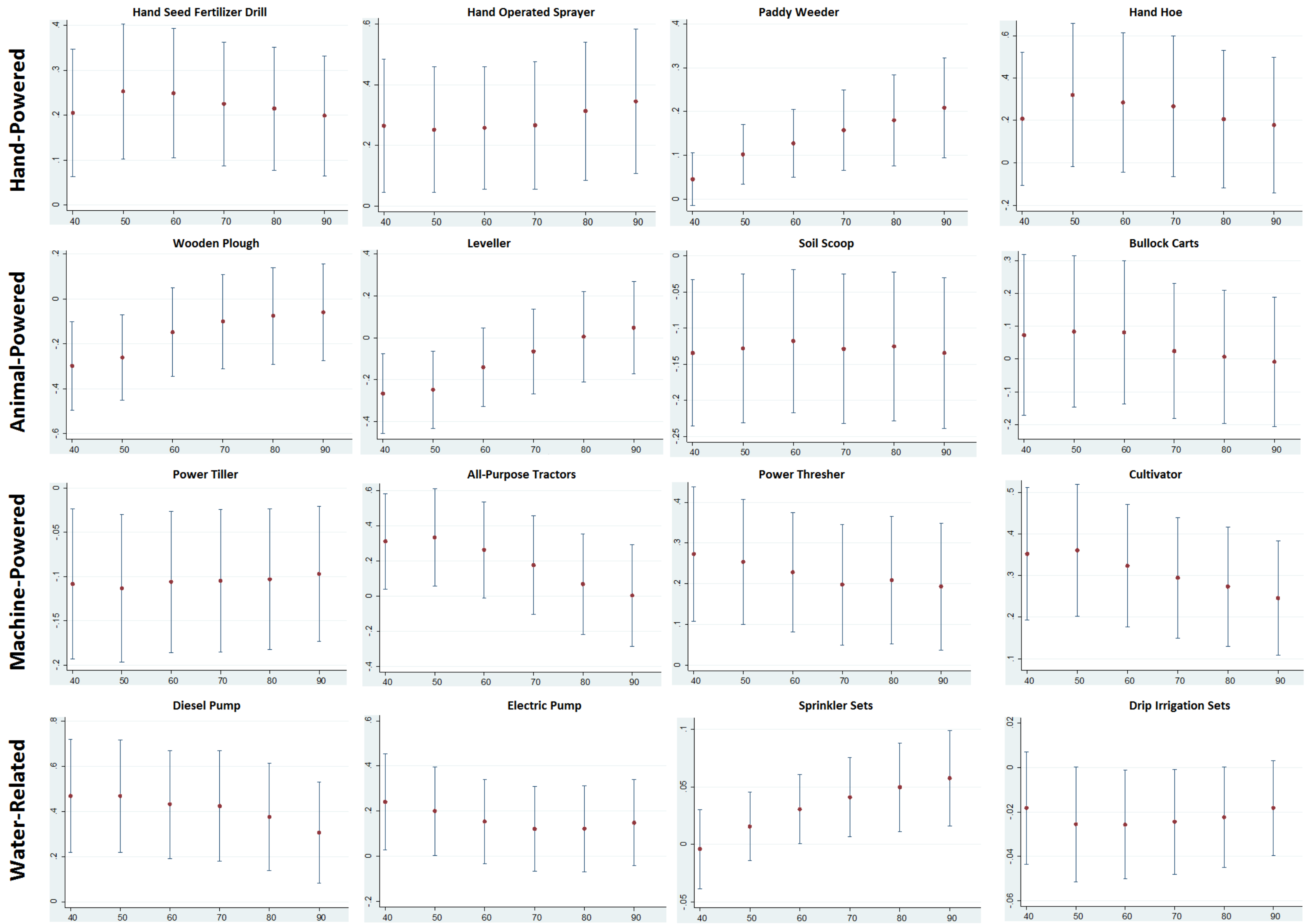

Figure 10: Estimates of jumps in technology use at NREGA cutoff by technology type

	Avg # of Farms per District	% of Total	Avg Acres Farmed per District	% of Total	Average Farm Size	Average Plot Size	Plots per Farm	% of Farms Using Technology in 2004	% of Farms Using Technology in 2007
Marginal (below 2.5)	123	0.64	128	0.21	1.21	0.86	1.67	71.79	58.66
	(139)		(130)		(0.30)	(0.41)	(0.92)	(28.20)	(26.64)
Small (2.5 - 5)	36	0.19	126	0.20	3.45	1.78	2.75	74.69	67.35
	(33)		(118)		(0.24)	(0.94)	(2.22)	(28.55)	(27.19)
Semi-Medium (5 - 10)	21	0.11	144	0.23	6.57	2.75	3.88	74.27	72.13
	(22)		(150)		(0.49)	(1.79)	(3.54)	(30.35)	(27.21)
Medium (10 - 25)	10	0.05	147	0.24	13.44	4.60	5.14	74.88	74.93
	(14)		(207)		(1.47)	(3.48)	(4.57)	(33.15)	(27.20)
Large (25 and above)	2	0.01	74	0.12	34.78	10.09	6.42	75.89	77.62
	(6)		(256)		(24.97)	(11.01)	(7.60)	(36.68)	(27.54)
All	192		619		4.16	2.29	2.33	71.94	62.59
	(169)		(628)		(3.90)	(2.46)	(1.45)	(26.95)	(26.21)

*Standard deviations in parentheses. Columns 2 and 4 are measured in thousands. N=371.

Table 1: Total farms and area farmed in India in 2007.

	OLS		DD		Panel FE	
	(1)	(2)	(3)	(4)	(5)	(6)
NREGA	0.0664***	0.0673***	0.00462	0.0171		
	(0.0189)	(0.0177)	(0.0296)	(0.0262)		
Post			-0.122***	-0.0744***	-0.125***	-0.0585**
			(0.0229)	(0.0200)	(0.0289)	(0.0255)
NREGA*Post			0.103***	0.0727**	0.149***	0.0997**
			(0.0383)	(0.0345)	(0.0534)	(0.0422)
Constant	0.645***	0.618***	0.718***	0.665***	0.714***	0.657***
	(0.0113)	(0.0118)	(0.0183)	(0.0159)	(0.0168)	(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

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2: OLS, DD & Panel Regression Results

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

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Panel Fixed Effect Regressions by Farm Size

	Jump in Adoption Rates			Jump in Treatment Probability			Treatment Effect		
	Coef.	SE	z	Coef.	SE	z	Coef.	SE	z
40 districts	-6.8	13.8	-0.49	60.8	32.9	1.84	-11.2	19.0	-0.59
50 districts	-4.2	12.3	-0.34	55.1	32.0	1.72	-7.7	19.4	-0.40
60 districts	-3.4	11.4	-0.30	46.3	32.4	1.43	-7.4	21.4	-0.35
70 districts	-3.5	10.0	-0.35	31.3	30.6	1.02	-11.3	26.0	-0.43
80 districts	-3.3	9.1	-0.36	25.5	28.3	0.90	-12.9	28.9	-0.45
90 districts	-1.1	8.5	-0.13	20.2	27.0	0.75	-5.6	38.1	-0.15
100 districts	0.0	8.0	0.00	17.6	26.0	0.68	-0.1	45.3	0.00

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

Table 4: Overall Regression Discontinuity Results with Treatment Effect Equal to Jump in Adoption Rates over Jump in Treatment Probability