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

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Abstract

Landless agricultural laborers and marginal farmers constitute much of India's poor. As population growth increases and more people enter an expanding rural labor force, either they must eke out a living in the rural sector or add to the growing pressure on the country's urban areas. Meanwhile, agricultural jobs are fewer and the corresponding wages have been persistently below subsistence levels. The Mahatma Gandhi National Rural Employment Guarantee Act (NREGA) takes aim at this problem by providing guaranteed employment to the rural poor at minimum wages in exchange for village public works. While the direct effects of this program appear clear—more income is being received by the poor, while village infrastructure is increasing—indirect effects within local agricultural economies abound. Theory developed in this paper shows the theoretical results of NREGA's impact on agricultural wages, while recent empirical evidence demonstrates a 3-5% increase in agricultural wages. This has the potential to affect farm owners. A farm owner that relies on this targeted unskilled labor to fill relatively inexpensive labor roles during peak agricultural production periods may now alter his production decisions by choosing to adopt labor-saving technologies as a result of an increasing labor-to-capital input price ratios. I specify a threshold model of technology adoption to illustrate this short-run result. In the long run, there may be further ripple effects in the rural economy, including increased agricultural productivity and still higher wages for rural laborers. I use difference-in-differences and regression discontinuity designs to test my theoretical results empirically. These empirical methods take advantage of the unique nature of the phased program rollout.

1 Introduction

Landless agricultural laborers and marginal farmers constitute much of India's poor. As population growth continues to increase and more people enter an expanding rural labor force, either they must eke out a living in the rural sector or add to the growing pressure on urban areas. Meanwhile, agricultural jobs are fewer and corresponding wages have been persistently below legal subsistence levels, remaining one of the lowest in the world (Venketeswarlu and Kalle 2012). The Mahatma Gandhi National Rural Employment Guarantee Act (NREGA) provides limited employment to the rural poor during slack agricultural production periods in order to combat this problem, while also developing rural infrastructure. In this research I discuss and evaluate the indirect impacts of the program on agricultural labor and technology markets.

Passed into law in 2005, NREGA guarantees up to 100 days of rural public works employment per year per person at state-level minimum wages. The law's main purpose is to provide an alternative source of income to agricultural laborers in slack production periods or drought years when less production on the farm means both fewer jobs and less income for workers. By contributing to public works, laborers add to the quantity and quality of local public goods, while developing infrastructure in the village for the long run. The types of activities undertaken in the program include water conservation, drought proofing, irrigation, land development, and rural connectivity.

Given the scale on which NREGA was implemented, the potential effects of this program abound. From the laborer's point of view, there are clearly the direct effects of higher income for the poor and an increase in development of village infrastructure. There may also be indirect effects in other areas of the economy, including rural labor markets, migration, and health and nutrition (over half of all NREGA workers are women). The payment of state-level minimum wages in agricultural areas, for example, has been shown to have upward pressure on agricultural wages. Several working papers have used data from India's National Sample Survey and Ministry of Agriculture to obtain a difference-in-differences estimates of 3-5% increases in casual/unskilled agricultural wages due to NREGA, with mixed results on the gender-neutrality of these effects (Imbert and Papp, 2013; Berg et al., 2012; Azam, 2012; Shah, 2012). There has recently been speculation that migration from rural areas to urban parts of India has slowed due to the program and increased urban wages.

Farm owners, on the other hand, often depend on this unskilled labor that is being targeted by NREGA. Changes in a worker's income and migration patterns may have an impact on farm operation decisions. For example, a farmer that relies on unskilled labor to fill relatively inexpensive labor roles during peak agricultural production periods may now choose to adopt labor-saving technologies as a result of an increasing labor-to-capital input price ratio. This alters both the labor and technology markets in the short run. I employ a threshold model of technology adoption to hypothesize that farmers will adopt labor-saving technology as a result of the program. In the long run, there may be further ripple effects in the rural economy, including increased agricultural productivity, better infrastructure and higher agricultural wages.

In order to identify the short run impact of NREGA on technology adoption, I consider the use of difference-in-differences and regression discontinuity designs. These methods take advantage of the unique nature of the program rollout in India over three phases. Phase I began in February 2006 and covered the 200 poorest districts in the country as measured by the country's Backwardness Index (BI), which uses three district-level agricultural indicators from the 1990s to rank all 593 districts of India. The program was extended to the next 150 poorest districts in 2008 and then to the rest of the country two years later.

The primary econometric concern with using a simple linear regression to identify the effect of NREGA on technology adoption is reverse causality: while one may expect NREGA to increase the use of technology in a district, it is also possible that districts with lower levels of technology to begin with are poorer and more likely to be eligible for the first phase of NREGA. To address this, I look at percent changes in technology use over time in districts that had NREGA versus those that did not. This controls for both differing levels of technology use and time trends in each district.

Data from the Indian Ministry of Rural Development specifies all NREGA projects by district. I consider NREGA project type when estimating the effect on technology adoption because increased village infrastructure can impact farm-level decisions, as well. For example, NREGA irrigation activities in a village may lead farmers to alter their water-related technology use. Rural connectivity may lead to more complete labor markets, thus affecting hired wages. I can control for these various project types in my analysis. Agricultural census data and the India Human Development Survey also provide control variables such as cultivable land per district, cropping patterns, credit availability, information access, education levels, and gender of farm owners.

I also specify a regression discontinuity design. This method is particularly well-suited for a program rollout of this nature, where exogeneity of NREGA treatment with the outcome of interest is not required. Furthermore, the assumption that districts just above and below the treatment cutoff are highly similar solves omitted variable bias. The main problem with using an RD design is typically that the trigger variable (in this case, the BI) must be non-manipulable by the beneficiaries of the treatment. In the case of NREGA, it is not possible that district governments could have manipulated their performance in the 1990s in anticipation of a program designed in 2005.

Results obtained in ongoing analysis from this research can demonstrate important lessons for developing countries wishing to provide security for their poorest citizens and develop rural infrastructure, while also incentivizing technology adoption and productivity growth. In the case of NREGA, all of these objectives may be achieved despite only the first two being intended. This is especially important as countries, both developing and developed, try to balance productivity growth and poverty alleviation.

2 Background & Literature Review

In this section I first describe the motivation behind NREGA and its goals in reducing poverty. I then look more closely at ongoing studies of NREGA's effect on labor markets, as well as an earlier set of studies revolving around a 1980s state-level employment guarantee in India. In Section 2.3, I review the literature on determinants of technology adoption, specifically those pertaining to labor-saving technologies. In general, recent studies have not focused much on the role of labor market dynamics on labor-saving technology adoption. Finally, since I consider how both the volume and different types of NREGA projects that are undertaken in villages may also affect labor and technology markets in both the short and long run, I review several studies, mostly in India, on the effect of infrastructure development on labor and capital acquisition.

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 arguably fits better 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]

[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.

Finally, NREGA 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 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 Guarantee and Agricultural Labor Markets

Ongoing analyses of NREGA's effects in the labor market show mixed results. Most studies have shown positive impacts on agricultural wages due to NREGA.

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. Of these, three studies used difference-in-differences estimation to find 3-5% increases in agricultural wages due to the program. finds the only private sector impacts occur during the dry season. finds that impacts are the same for men and women. Shah (2012) estimated a 6.5% increase in agricultural wages and additionally found that a one standard deviation increase in infrastructure 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, indicating no change in labor force makeup.

Most of these studies do not develop theoretical models explaining how an employment guar-

[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.

antee 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 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

[3]Even in the case where $w_P \leqslant w_N$, there should theoretically 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.

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 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 detailed specifications 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 and determines 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.

3.1 Agricultural Wages

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

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 what changes in these producer and laborer optimization problems result with the introduction in NREGA. 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 are 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 in 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 $S_A \rightarrow S'_A$ 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.

Threshold Model

The threshold model can be depicted as in Figure (**??**), which shows two production functions in output-labor space that correspond to the old technology and the new, labor-saving technology.

There is a specific labor threshold, L^*, and associated wage level where a farmer finds it profitable to make the switch from an old technology, T_1 (labor-intensive), to a new technology, T_2 (labor-saving). At low wage levels (w_1), it is better to keep the old technology because farm owners are willing to pay small wages. However, when wages increase to w_2, a farmer can either produce at a lower level of output, q_1, or switch to T_2 and produce at q_2. (Note: Figure **??** should have w_1/p and w_2/p instead of w_1 and w_2, respectively, where p is the output price and the space on the x-axis between the origin and the beginning of curve T_2 should be labeled as the fixed cost, F, of adopting the new technology).

Sunding and Zilberman (2001) discuss a method to model this 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.

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 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

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

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.

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

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.

First, if the farm owner adopts the new labor-saving technology, the long run demand for agricultural labor may shift in, especially if technology choices are irreversible. Sunding and Zilberman (2001) describe F as partly embodying the upfront cost of new, indivisible equipment (the other part being information and learning). However, agricultural capital markets in India are characterized by custom-hiring of technology that incurs mostly variable costs, especially in small farm areas. (There may be some fixed costs that capital owners incur when custom-hiring out to farm owners). This decreases the value of F to include virtually only information and learning costs to the farm owner. And when labor-saving technologies are relatively well-known, such as for a tractor or combine harvester, and owners of the capital are doing most of the operation, even this cost may be quite small. This means that in the long run a farmer may be able to more easily reverse his decision 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 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 secon possibility is that, to the extent that technology adoption leads to higher agricultural production in villages and to the extent that that NREGA is successful in building public infrastructure, demand curves for agricultural labor could actually shift out, since demand is a function of income, $D = D(Y)$. This is represented by point G in the Figure 3, where the long run level of agricultural labor could range anywhere in the neighborhood of L^A and both agricultural and total labor market wages approach 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

4.1 OLS

In this section I describe an approach for estimating NREGA's impact on technology adoption.

First, consider a simple OLS model of the form

$$TA_i = \alpha_i + \beta_i * NREGA_i + \gamma_i * X_i + \varepsilon_i,$$

where TA is the number 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 any affect that the NREGA program has on technology adoption in district i. However, 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), then there is an econometric concern of reverse causality, where NREGA technology levels in the district also determines whether the village receives NREGA treatment.

Thus, OLS estimates of the effect of NREGA participation on technology adoption rates would be biased. To address this problem, 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

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 equation to be estimated is

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

where TA represents technology adopted in district i in year t, $NREGA$ is a dummy variable that equals 1 if the district qualified for NREGA that year and t is a dummy variable equaling 1 for observations after 2006. This accounts for both differing initial levels of technology use by district and also the general time trend between periods.

It is possible that there were trends that affected the treatment and control districts differently in the years between 2001 and 2007. That is, the parallel trends assumption that typically accompanies the DD approach may not hold. There are at least a couple ways to test this. First, one can identify any major events in the time period that might affect trends in technology adoption for the poor differently than for the rich. Second, a placebo test of differences in technology adoption rates of NREGA districts can be done using l996 and 2001 data. Any significant differences during this period can be attributed to changing trends over time between poor and rich districts.

The main coefficient of interest in Equation 15 is δ, which gives the treatment effect of NREGA on technology adoption net of time trends. The coefficients β and γ are the individual effects of NREGA not accounting for time trends and of time alone without accounting for the difference in treatment, respectively, while α is the intercept representing the average technology adoption level of non-NREGA villages before the rollout.

One problem with equation (15) is that it assigns all NREGA districts the same value despite the variation in intensity of carrying out the program in each district. A second DD specification uses the variation in NREGA workdays per year by district to estimate NREGA's impact. The treatment variable now becomes the product of $NREGA$ and $days$ (as in Banerjee 2007) and is incorporated into the the difference-in-differences equation as follows:

$$TA_i = \alpha + \beta * NREGA_i + \gamma * yr_i + \delta * (NREGA * days)_i * yr_i + \varepsilon_i, \tag{16}$$

where *days* is the total number of NREGA workdays in the district for that year.

It is important for this specification that the number of NREGA days not be correlated with the error term. That is, the number of days cannot be correlated with any unobserved variables that may also affect trends in technology adoption for one group and not another. This is most likely if size of the district matters. To address this, I divide NREGA days worked by the total population of the district to get the number of NREGA days per capita, or $dayspc = \frac{NREGA\,days}{village\,population}$, and modify equation (16) to

$$TA_i = \alpha + \beta * NREGA_i + \gamma * yr_i + \delta * (NREGA * dayspc)_i * yr_i + \varepsilon. \tag{17}$$

Other possible causes of endogeneity of the *days* or *dayspc* variable with technology adoption are lack of local government capacity to implement NREGA or corruption, as well as lack of information on technologies and credit constraints. Ideally, changes in the ratio of NREGA days per person in a village should only result from laborer preferences. For example, if a villager worked 90 days for NREGA this year instead of 100, it is because of his or her preferences, not because local leaders either do not have the capacity or will to give villagers 100 days. This would be a problem in estimating equation (17) because it would affect trends for the treatment group more than the other.

4.3 Regression Discontinuity Design

An RD design solves some of these identification challenges by assuming that villages around a treatment threshold are the same except for a certain exogenous factor which assigns the treatment to some and not to others. For NREGA, this threshold is the Planning Commission's Backwardness Index (BI), which ranked the 447 poorest districts in India using wages, productivity and SC/ST[7] population percentage from 1990-1997. The first 200 districts in the BI received NREGA funds in 2006, while 150 began the program in 2008.

RD does not require that the variation in the treatment variable be exogenous to the outcome

[7] Scheduled Caste/Scheduled Tribe

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 this case, the government used measures from the 1990s to determine whether villages received NREGA treatment in 2006. 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.

The RD equation takes the form

$$TA_i = \alpha_i + \beta_i * NREGA_i + \gamma_i * BI_i + \varepsilon_i, \tag{18}$$

where $\alpha_i = TA_{0i}$, or the technology adoption rate absent the NREGA program; $\beta_i = TA_{1i} - TA_{0i}$, or the treatment effect on technology adoption at the threshold level; $NREGA$ is the binary treatment variable; and BI is the Backwardness Index that was used to determine cutoffs for the first rollout of NREGA funds. I use the sharp RD design as opposed to the fuzzy design because districts become part of NREGA in a deterministic way solely dependent on the its BI score (Angrist and Pischke). Formally, this is expressed as $NREGA_i = f(BI_i)$, where the argument takes on a continuum of values and the function is discontinuous at BI_0. In order to conduct an RD and have enough power to identify relationships, a local linear regression is used in the RD estimation equation so that districts closer to the threshold get larger weights.

5 The Data

The data contains the estimated number of agricultural machines used in each district of India in 2002 and as well as the number of operational holdings using agricultural machines in 2007. All of this data is sub-divided by operational holding size, e.g., marginal, small, medium, and large farmers (see table 1). In addition, there is information on total area of operational holdings (i.e., the number of farms), the average area farmed in a district, the number of plots, plots per farm and average area of plot. Additional information includes credit and the length of any loans, educational status, age, household size, irrigation facilities, types of NREGA infrastructure projects undertaken, and the districts covered under each NREGA phase.

References

Azam, M. 2012. "The impact of Indian job guarantee scheme on labor market outcomes: Evidence from a natural experiment.", pp. .

Basu, A. 2011. "Impact of rural employment guarantee schemes on seasonal labor markets: optimum compensation and workers' welfare." *Journal of Economic Inequality*, pp. 1–34, 10.1007/s10888-011-9179-y.

Berg, E., S. Bhattacharyya, R. Durgam, and M. Ramachandra. 2012. "CSAE Working Paper WPS/2012-05.", pp. .

Besley, T., and A. Case. 1993. "Modeling Technology Adoption in Developing Countries." *The American Economic Review* 83:pp. 396–402.

Binswanger, H.P., S.R. Khandker, and M.R. Rosenzweig. 1993. "How infrastructure and financial institutions affect agricultural output and investment in India." *Journal of Development Economics* 41:337 – 366.

Conley, T.G., and C.R. Udry. 2010. "Learning about a New Technology: Pineapple in Ghana." *The American Economic Review* 100:35–69.

de Janvry, A., M. Fafchamps, and E. Sadoulet. 1991. "Peasant Household Behaviour with Missing Markets: Some Paradoxes Explained." *The Economic Journal* 101:pp. 1400–1417.

Dreze, J.H. 1990. *The political economy of hunger*, Clarendon Press - Oxford, vol. 1, chap. 1. Famine Prevention in India. pp. 13–123.

Fan, S., P. Hazell, and S. Thorat. 2000. "Government Spending, Growth and Poverty in Rural India." *American Journal of Agricultural Economics* 82:1038–1051.

Feder, G., R.E. Just, and D. Zilberman. 1985. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development and Cultural Change* 33:pp. 255–298.

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

Frisvold, G.B. 1994. "Does supervision matter? Some hypothesis tests using Indian farm-level data." *Journal of Development Economics* 43:217 – 238.

Harriss, B. 1972. "Innovation Adoption in Indian Agriculture-the High Yielding Varieties Programme." *Modern Asian Studies* 6:71–98.

Hicks, W.W., and S. Johnson. 1979. "Population growth and the adoption of new technology in colonial Taiwanese agriculture." *Journal of Development Studies* 15:289–303.

Imbert, C., and J. Papp. 2013. "CSAE Working Paper WPS/2013-03.", pp. .

Just, R.E., and D. Zilberman. 1988. "The effects of agricultural development policies on income distribution and technological change in agriculture." *Journal of Development Economics* 28:193 – 216.

Minten, B., and C.B. Barrett. 2008. "Agricultural Technology, Productivity, and Poverty in Madagascar." *World Development* 36:797 – 822.

Muellbauer, J., and R. Portes. 1978. "Macroeconomic Models with Quantity Rationing." *The Economic Journal* 88:pp. 788–821.

Narayana, N., K.S. Parikh, and T. Srinivasan. 1988. "Rural works programs in India: Costs and benefits." *Journal of Development Economics* 29:131 – 156.

Olmstead, J. 1998. "Emerging markets in water: investments in institutional and technological change." PhD dissertation, Department of Agricultural and Resource Economics, University of California, Berkeley.

Osmani, S. 1990. "Wage determination in rural labour markets: The theory of implicit cooperation." *Journal of Development Economics* 34:3 – 23.

Qaim, M., and A. de Janvry. 2003. “Genetically Modified Crops, Corporate Pricing Strategies, and Farmers’ Adoption: The Case of Bt Cotton in Argentina.” *American Journal of Agricultural Economics* 85:pp. 814–828.

Sandmo, A. 1971. “On the Theory of the Competitive Firm Under Price Uncertainty.” *The American Economic Review* 61:pp. 65–73.

Shah, V. 2012. “Managing Productivity Risk Through Employment Guarantees: Evidence from India.”, pp. .

Spencer, D.S.C., and D. Byerlee. 1976. “Technical Change, Labor Use, and Small Farmer Development: Evidence from Sierra Leone.” *American Journal of Agricultural Economics* 58:pp. 874–880.

Sunding, D., and D. Zilberman. 2001. “Chapter 4 The agricultural innovation process: Research and technology adoption in a changing agricultural sector.” In B. L. Gardner and G. C. Rausser, eds. *Agricultural Production*. Elsevier, vol. 1, Part A of *Handbook of Agricultural Economics*, pp. 207 – 261.

Thurow, A.P., W.G. Boggess, C.B. Moss, and J. Holt. 1997. “An Ex Ante Approach to Modeling Investment in New Technology.” In D. D. Parker and Y. Tsur, eds. *Decentralization and Coordination of Water Resource Management*. Springer US, vol. 10 of *Natural Resource Management and Policy*, pp. 317–338.

Zimmermann, L. 2012. “Labor market impacts of a large-scale public works program: evidence from the Indian Employment Guarantee Scheme.”, pp. .

Tables

2002										
Farm size *(ha)*:	# of Farms	% of Tota	Area Farmed ('000s ha)	% of Tota	# of Plots ('000s)	Plots per Farm	Area per Plot (ha)	Area per Farm	Machines Used ('000s)	% of Tota
Marginal *(below 1.0)*	125 *(134)*	61%	52 *(51)*	18%	230 *(287)*	1.9 *(1.7)*	0.3 *(0.2)*	0.5 *(0.1)*	812 *(1203)*	53%
Small *(1.0 - 1.99)*	41 *(38)*	20%	58 *(55)*	20%	110 *(120)*	2.9 *(2.9)*	0.7 *(0.4)*	1.4 *(0.2)*	324 *(413)*	21%
Semi-Medium *(2.0 - 3.99)*	26 *(25)*	12%	69 *(69)*	24%	87 *(93)*	4.1 *(4.1)*	1.0 *(0.7)*	2.6 *(0.4)*	224 *(278)*	15%
Medium *(4.0 - 9.99)*	12 *(14)*	6%	70 *(85)*	25%	54 *(67)*	5.9 *(6.3)*	1.6 *(1.3)*	5.3 *(1.0)*	129 *(174)*	8%
Large *(10 and above)*	2 *(6)*	1%	35 *(114)*	12%	13 *(27)*	8.2 *(9.7)*	3.2 *(3.3)*	13.8 *(8.3)*	32 *(84)*	2%
All	206 *(169)*		283 *(272)*		495 *(471)*	2.6 *(2.1)*	0.9 *(0.9)*	1.7 *(1.5)*	1,522 *(1859)*	
2007										
Farm size *(ha)*:	# of Farms	% of Tota	Area Farmed ('000s	% of Tota	# of Plots ('000s)	Plots per Farm	Area per Plot (ha)	Area per Farm	Farms Using Machines ('000s)	% of Tota
Marginal *(below 1.0)*	123 *(139)*	64%	52 *(53)*	21%	200 *(222)*	1.7 *(0.9)*	0.3 *(0.2)*	0.5 *(0.1)*	592 *(592)*	55%
Small *(1.0 - 1.99)*	36 *(33)*	19%	51 *(48)*	20%	94 *(97)*	2.7 *(2.2)*	0.7 *(0.4)*	1.4 *(0.1)*	228 *(270)*	21%
Semi-Medium *(2.0 - 3.99)*	21 *(22)*	11%	58 *(61)*	23%	74 *(83)*	3.9 *(3.5)*	1.1 *(0.7)*	2.7 *(0.2)*	153 *(192)*	14%
Medium *(4.0 - 9.99)*	10 *(14)*	5%	59 *(85369)*	24%	46 *(64)*	5.1 *(4.6)*	1.9 *(1.4)*	5.4 *(0.6)*	80 *(118)*	8%
Large *(10 and above)*	2 *(6)*	1%	30 *(104)*	12%	11 *(25)*	6.4 *(7.6)*	4.1 *(4.5)*	14.1 *(10.1)*	16 *(42)*	1%
All	192 *(169)*		251 *(254)*		425 *(381)*	2.3 *(1.5)*	0.9 *(1.0)*	1.7 *(1.6)*	1,069 *(1104)*	

Table 1: Farm, plot and technology summary statistics at district level by farm size and year

Figures

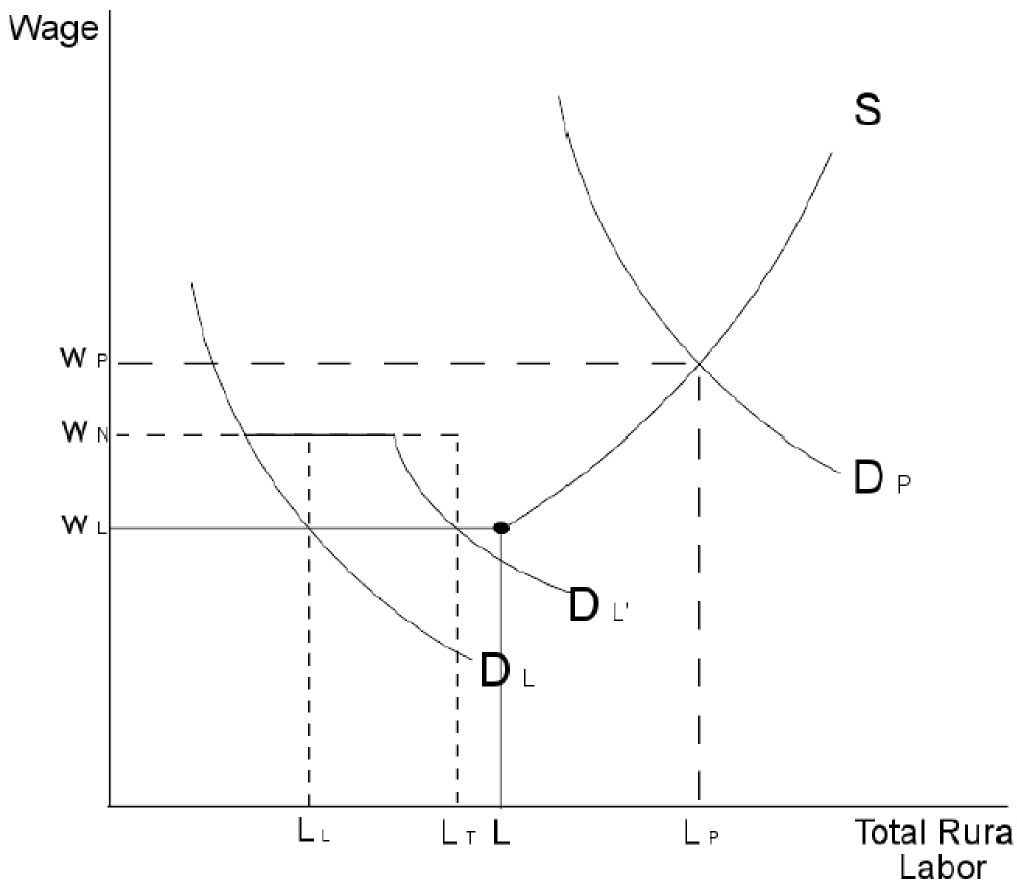

Figure 1: Agricultural and NREGA Labor Supply with Peak and Lean Season Demand (Narayana, Parikh, and Srinivasan, 1988)

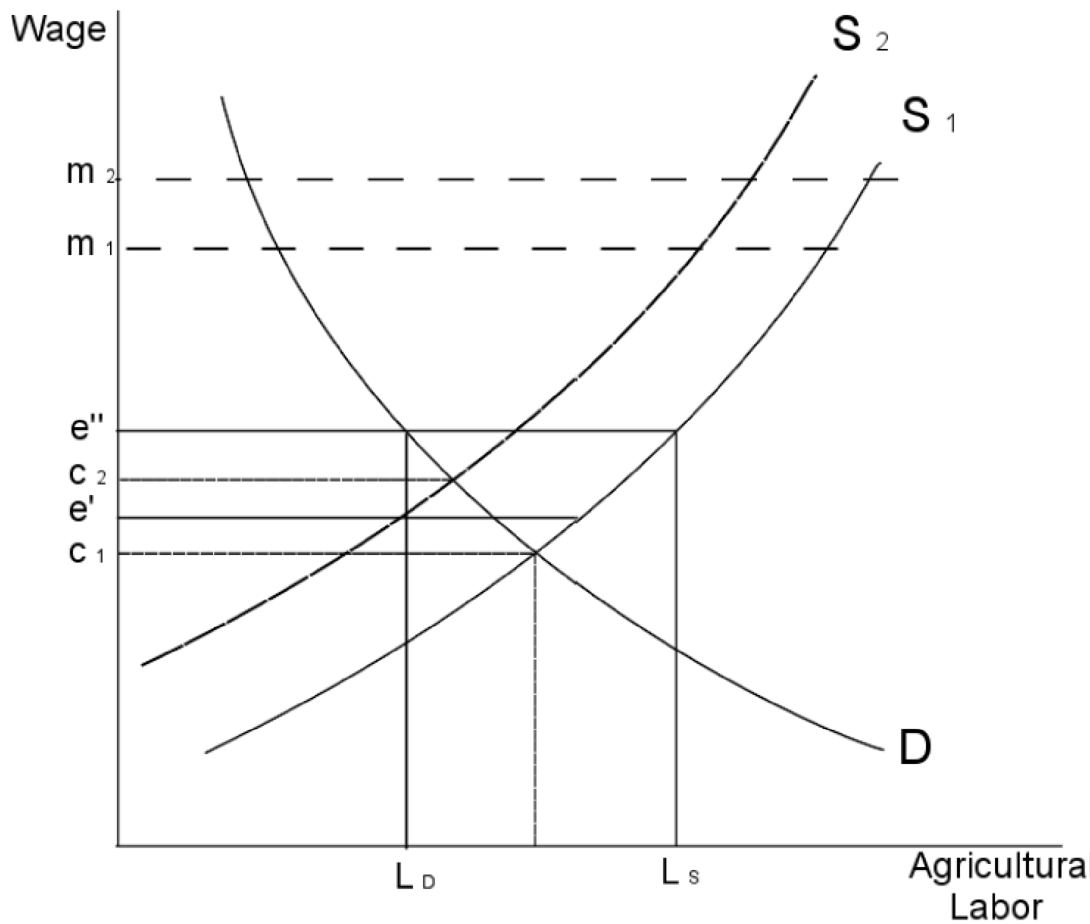

Figure 2: Implicit Cooperation Amongst Workers Leads to Equilibrium Wage Above Competitive Wage (based on Osmani (1990)

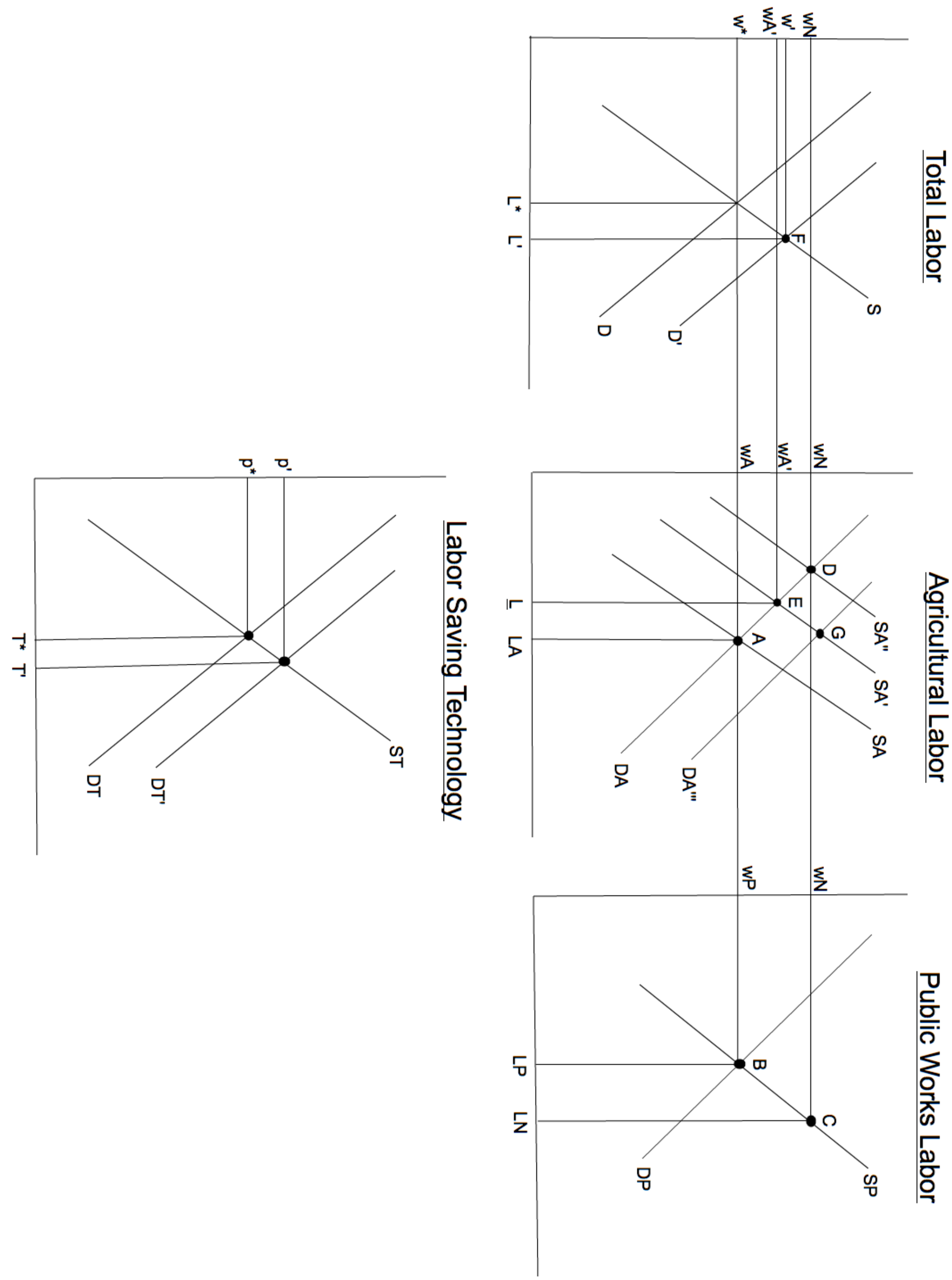

Figure 3: Short and Long Run Effects of NREGA on Rural Labor and Technology Markets