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Impact of NREGS on Forest Cover

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Introduction

Workfare programs have been common policy instruments adopted in developing countries to reduce poverty, increase resilience especially in times of agricultural lean seasons, and improve rural infrastructure. “Self-selection” by participants in these programs reduce the information problems governments face in targeting the right households that require financial assistance (Besley and Coate, 1992; Sukhtankar, 2016). While most of the studies have explored the efficacy of these programs in improving social indicators, few have looked at the impacts of these or cash transfer programs on natural resources and the environment (eg. Alix-Garcia et.al, 2013). In the present paper I propose to explore the links between the National Rural Employment Guarantee Scheme (NREGS), a workfare program in India and natural resources specifically forests. Public works programs like NREGS can affect utilization or conservation of natural resources both directly, by successful implementation of conservation programs, and indirectly, by reducing poverty and improving infrastructure. The initial objective of this paper is to estimate the impact of NREGS on greenness and forest cover. The next objective will be to model how NREGS affects household level decisions regarding consumption, agricultural pattern, migration, which in turn affect resource utilization.

The National Rural Employment Guarantee Scheme (NREGS) is the largest workfare program in the world. It aims to reduce poverty by providing yearly public works employment to rural households at minimum wages. NREGS became a law in 2005 and was implemented first in 2006. The Act guarantees up to 100 days of employment in rural public works to any household within 5 kilometers of residence and within 15 days from the date of application. The state-level minimum wage rates, which are around USD 2 a day, determine the wages given to those that are employed by these programs. Remuneration depends on state-specific minimum wages, usually about US$2 per day. NREGA is thus an attempt at increasing and stabilizing the disposable income of unskilled workers since they are at risk of facing higher food prices and unemployment during drought or agricultural slack seasons. The public works projects undertaken by NREGA have primarily focused on irrigation and road infrastructure building and maintenance. Assessment studies have looked at the impact of NREGS on afforestation and environmental vulnerability reduction (Tiwari et.al, 2011; Esteves et.al, 2013; Sebastian and Azeez, 2014). However, these are appraisal studies focusing on NREGS implantation in specific areas of districts of India, and thus do not give a picture of the effectiveness of NREGS on resource conservation at a macro level. This study attempts to fill the gap in the current literature on the impact of workfare programs like NREGS on natural resources.

In the next section the relevant literature is reviewed, followed by a discussion of the data and methodology and future research.

Literature Review

Public works programs are expected to have both micro and macro level effects (Sukhtankar, 2016). Micro level effects involve households making decisions given their increased budget constraints due to greater number of days of employment, while macro level effects are observed through creation of public works such as improved irrigation infrastructure or roads, and their effects on resource utilization by households. Three strands of literature will be reviewed here to help us analyze the relationship between NREGS and resource utilization: impact of poverty reduction on environment; the impact of cash for work or similar programs on environment and agriculture; and the effects of NREGS on various outcomes such as income, employment, consumption, and migration.

Impact of Poverty Reduction on Environment

Numerous studies have looked at the relationship between poverty reduction and its impact on environment. Workfare or CCT programs aim primarily to reduce poverty. Thus, successful implementation of NREGS is expected to have positive impacts on environment. However, the effects of NREGS on migration, infrastructural development, etc. also has indirect effects on resource utilization. Foster and Roszenweig (2003) utilized a panel data consisting of 250 villages in India to determine the relationship between income growth and forest conservation in India. Contrary to widely held belief that agricultural productivity and time price were the reasons for decreasing trends in deforestation, they found that with rising household incomes, there was increased demand for forest products, and thus consequent increases in household level incentives for forest conservation. On the other hand, Dasgupta et.al (2003) explored the poverty-environment nexus and found that a shrinking resource base aggravates poverty which in turn leads to further environmental degradation. Bhattacharya and Innes (2008) also found that environmental decline is associated with increased rural population and net rural in-migration. This in turn further deteriorates environment. The environment-poverty nexus in India implies a bidirectional link between the two, with one spurring the other (Bhattacharya and Innes, 2006). Endogeneity of income is a concern in the literature on relationship between poverty reduction or income increases and deforestation (Alix-Garcia, 2013). In a meta-analysis of the literature on possible causes of deforestation, Angelsen and Kaimowitz (1999) finds no substantial empirical evidence between poverty and deforestation. While factors like off-farm employment could have simultaneous impact on both poverty and deforestation, increasing incomes could also boost deforestation if the latter is associated with increased investments which richer household can afford.

The impact of CCT or cash for work programs on environment and agriculture

Most of the studies on NREGA and other workfare programs have focused on the impact of these programs on poverty alleviation, income stabilization and rural infrastructure. However, few studies have looked at the impacts of such programs on the environment. Alix-Garcia et al (2011) identified the impacts of household income increases due to CCT under Oportunidades on deforestation. They use a regression discontinuity design given there is a discontinuity created by the eligibility rule of the program. Due to increases in the consumption of land intensive food like beef and milk, and since no change in consumption of products directly or indirectly related to forest is detected, they concluded that deforestation occurs due to changes in consumption patterns. The probability of deforestation occurring due to household level increases is even higher among those who were deforesters to begin with.

In terms of farm level decision making, Bhargava (2014) explored the effects of NREGA on agriculture technology and prices in Eastern UP and Bihar in India. He found that simple agricultural technology that reduced manual labor was adopted by farmers in the villages where NREGA was implemented. Moreover, prices of agricultural products increased since availability of casual labor fell due to increased asking wage rates of the laborers. The Planning Commission in India had used a Backwardness Index to rank the districts by their state of development. Since the low-ranking districts were the ones where NREGS was implemented initially (in the first phase), this paper utilized the index as the exogenous factor that was responsible for the assignment of the treatment (here NREGS participation) and used a fuzzy regression discontinuity design to analyze the effects of the program on technology adoption. Shah (2012) studied the risk mitigation effects of NREGS. In rural areas in developing countries where there is a lack of insurance mechanism to protect farmers against risk, policies like workfare programs help reduce risk. He finds that the sensitivity of wages to productivity shocks fall by 30% for a 1 standard deviation increase in the district's rural infrastructure under NREGS. Moreover, a program like NREGS helps farmers to make ex-ante decisions regarding cultivation. Thus, a farmer would increase the share of cultivation of high risk high return crops. Such changing agricultural decisions might have impacts on resource conservation as well.

The effects of NREGS on Various Outcomes

Many studies have been done to study the efficacy of NREGA in reducing poverty or improving employment in India. Sukhtankar (2016) gives a detailed discussion on the scope and limitations of studies on NREGS. Here we look at some of the more recent articles that have looked at the effects of NREGS on labor participation, wage rates, consumption, and agriculture. Azam (2012) showed that NREGA had a positive effect on the female participation in workforce and female wage rates. A representative national level sample was used from NSS data and difference-in-difference framework was used since the program was introduced in a phase-wise manner over the districts. However, his study did not consider the effects of migration. Thus, it is possible that female labor participation rates could have increased due to males migrating out of villages. In a couple of studies, Imbert and Papp (2014, 2013) showed that NREGA has redistributive effects in the rural effects from households that are net labor buyers to those that are net labor sellers. Hence there has been resistance to the implementation of NREGA by larger farmers in villages. NSS Employment Survey along with data on roads from PMGSY were utilized for these studies. Controlling for district level socio-economic outcomes as well as number of kilometers of roads built under the PMGSY scheme, the authors use a difference-in-difference technique. They also find that while short term migration to urban areas decreases, there are no long-term effects of migration. Thus, the authors suggest that there might be short term pressure on forest resources due to decreased migration.

The above papers used difference in difference (DID) approach to estimate outcomes of NREGA participation. Some of papers also used a triple differences approach which control for effects on outcome variables that are not caused by participation in NREGS. Using a 3-year household level panel data for Andhra Pradesh, Liu and Deininger (2010), found positive impacts of NREGS on consumption expenditure, intake of protein and energy, and asset accumulation. They conclude that the short run effects on the households participating in NREGS were greater than the program costs. They used a 3-round panel of 4,000 households from Andhra Pradesh. Along with a DID approach, the authors combine triple differences with propensity score matching to control for any bias due to "interaction between observables and the difference of subsequent changes over the two periods" of the study. Ravi and Engler (2014), in a village level analysis in Andhra Pradesh found that in addition to increased food and non-food expenditures, NREGS had a consequent improvement in food security through reduction in the frequency of skipped meals by households. Moreover, in terms of asset creation, the program improved savings among the households. They estimate the impact of NREGS participation on household level outcomes using a two-step difference in differences approach. Since the survey was done when the program had already been implemented, the authors estimate post-intervention growth rates of outcomes instead of the treatment effect of the introduction of NREGS. As a second step of their estimation strategy, the authors compute triple difference estimates which can control for the effects that do not depend on NREGS. Non-participants are matched to participants using propensity scores after which groups of those who were denied and those who were given employment were compared.

Data and Methodology

Vegetation

A simple measurement of forest cover or a "measurement of greenness" would be the Normalized Difference Vegetation Index (NDVI). NDVI is calculated as a difference between the near-infrared radiation and the visible radiation divided by the sum of the two. While healthy vegetation absorbs most of the visible radiation and reflects a substantial portion of the infrared radiation, sparsely green areas do the opposite. Thus, a higher value of NDVI corresponds to a healthier vegetation (NASA). NDVI is a satellite imaging data that is measured either on a 10-day or a 30-day composite basis by NASA in a given pixel (1 square km of land). The 30-day measure can control for errors caused by say clouds, but remove certain detailed spatial resolutions. NDVI is a popular measure of vegetation health and is robust to topographic differences, the illumination angle of the sun, and have (Foster and Rosenzweig, 2003).

Rainfall

Monthly rainfall data for the districts of India are obtained from Indian Meteorological Department's Rainfall Statistics of India for the relevant years. There are about 3500 stations all over India which measure rainfall. The data also provides information on how much the measured rainfall of a region has deviated from Rainfall Normals – averages based on rainfall records from 1951 to 2000. This gives us an opportunity to control for excessive rainfall or droughts.

Backwardness Index

NREGS participation was based on district level rankings in terms of Backwardness Index, an index created by the Planning Commission in the 1990's. The index is based on the following socio-economic and demographic indicators, proportion of population belonging to Scheduled Castes or Scheduled Tribes, agricultural wages and output per agricultural worker. The actual rankings have been obtained from Planning Commission reports while the list of districts participating in NREGS has been obtained from NREGA website.

NREGS was rolled out in three phases. The program was introduced to 200 districts in February 2006 under phase I, it was extended to 130 more districts in under the phase II in April 2007, and the program was introduced to remaining districts in India under phase III in April 2008. Unlike Mexico's PROGRESA, the NREGS does not have a randomly assigned rollout and the districts which were selected initially for the rollout were considerably poorer than those which belonged to the later phases of the rollout. Thus, analyses like those of Duflo (2000), and Miguel and Kremer (2003), cannot be utilized for studying NREGS. Given the nature of the roll-out of NREGS, let us consider some of the methodologies that can be used to analyze the problem that we have.

The dependent variable in the econometric specification is district level monthly composite-basis of NDVI. Under an OLS specification with district level controls and a dummy variable for NREGS implementation, it is assumed that the expected value of the error term is 0. However, it has been seen that districts that have large percentages of forest cover are more likely to be poorer and thus have NREGS implemented in the initial phases. Thus, there is endogeneity and factors that determine the extent of forest cover also in turn determine the chances of whether NREGS is implemented in a district in the initial phases (Bhargava, 2014). Given that the OLS parameter estimates will be biased, let us consider some empirical methodologies to analyze the problem.

Several studies have used a difference-in-difference methodology to look at the impact of NREGS participation on various outcomes. However, one of the pitfalls of using a difference-in-differences methodology is that the estimates will be biased if the "parallel trend" assumption is not satisfied (Duflo, 2013). For example, Imbert and Papp (2015a) found that the trends in the wages for the treatment and control groups were not parallel. Thus, we will have to check if the outcomes of the treatment (phase I and II) districts trend differently than the outcomes of the control (phase III) districts for a few years before the program started. Another problem in using DID is that since there is only a year or two of difference between the implementation of NREGS in treatment and control districts, therefore, we may not see much difference in the "intensity of treatment" (Sukhtankar, 2016). Moreover, forest cover might take some time to change, therefore differences in the changes may not be significantly different between the treatment and the control groups.

It is possible the treatment and control districts might not have parallel trends before program implementation, and therefore the difference-in-differences may not be a viable option. Regression discontinuity methodology can be utilized in such a situation. It assumes that there is an exogenous factor or algorithm that determines whether an observation belongs to treatment or control group, and that there is no difference between two observations at the threshold of the treatment except this factor (Bhargava, 2014). Zimmerman (2015) devised an algorithm to predict the chances of a district getting NREGS implemented based on state level cut-offs. It was able to predict NREGS implementation correctly for 80% of the districts. The paper utilized a fuzzy RDD model to predict the effects of NREGS on private and public wages. Although the districts which had NREGS implemented in the initial phases were more backward than the rest, there were political factors as well that determined which districts were to be selected for the initial phases (Sukhtankar, 2016; Chowdhury, 2014). Due to this reason and the fact that there was no one-to-one correlation between 200 poorest districts and NREGS participation, Bhargava (2014) utilized a fuzzy regression discontinuity model.

In the present study we will be utilizing a fuzzy RD model (FRD). In FRD, there is a discontinuous change in the probability of treatment at the cut-off, unlike the sharp RD models where discontinuity lies in the change in treatment. In this approach, the two stage least squares estimation can be used by instrumenting for whether the observation received the treatment or not (Lee and Lemieux, 2009). That is, in this study, whether the district had NREGS implemented in the 1st phase or the 2nd phase. In the next section, results are given in detail along with their discussion and scope for further work.

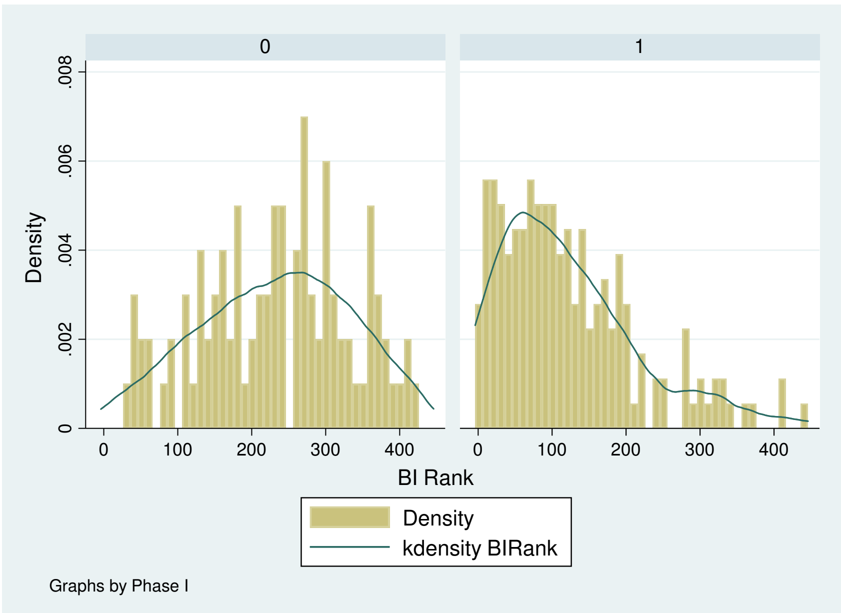
Results and Discussion

NREGS was first introduced in 200 backward districts of India in February 2006. While, the next 130 districts had NREGS introduced in April 2007. Another 117 districts had NREGS introduced under phase III in April 2008, and the rest had implementations later. The districts were chosen in terms of their ranks according to a Backwardness Index. However, as seen earlier, the criterion was not exactly followed as we see in the table below:

	Rank >200	Rank < or = 200	Total
Phase II	63	37	100
Phase I	28	151	179
Total	91	188	279

Moreover, around 30 districts that were included in phase I and 21 districts that were included in phase II did not have a Backwardness Index calculated for them. These districts are mostly from the poorer North-Eastern states and Kashmir. The Planning Commission had not ranked them most likely because the developmental issues and insurgency these districts face are very different from the rest of the districts in India (Planning Commission, 2003). Thus, there is not an exact one-to-one matching between how NREGS was introduced in the two phases, and how it should have been introduced ideally in terms of ranking of districts. Here are the histograms and kernel density plots (with widths of 10 bins each) for the districts that were treated (had

NREGS introduced in phase I) and not treated (had NREGS introduced in phase II). The panel on left shows that there is a substantial portion of the tail to the left of BI rank 200, while the panel on right shows that that there is some tail of the distribution to the right of rank 200. This reflects the imperfect assignment of treatment.



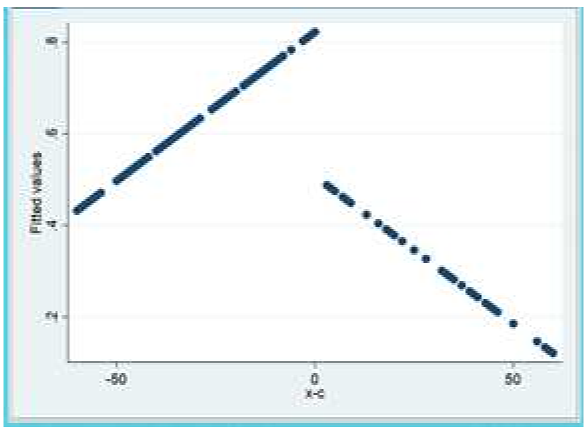
In the FRD design, we estimate the local average treatment effect over a bandwidth. The estimation is similar to that of 2SLS estimation. The estimation result depends on the choice of bandwidth and we estimate the local average treatment effect (LATE). Bhargava (2014) considered bandwidths between 40 and 90 districts on each side of the cut-off. In this study we focus on estimates with a bandwidth of 60 relative ranks on both sides of the cut-offs. One of the next steps in our analysis will be to estimate the effect of the program at other bandwidths.

In order to understand the discontinuity in the probability of treatment at the cut-off (the Backwardness Index rank of 200), I regress the actual treatment (*D*) on the eligibility based on cut-off (*T*) based on the cut-off, and the difference between the rank of the observation and the cut-off of 200 (*x*-*c*), and the interaction between the two explanatory variables. This is one of the equations of the two-equation system in 2SLS estimation.

$$D = \alpha + \beta T + f(x - c) + \gamma T * (x - c) + \upsilon$$

	Coefficients and SEs
Eligibility (T)	.315*** (0.192)
BI rank – cut-off (x-c)	-.006 (0.0061)
T*(x-c)	.0129*** (0.0078)
Constant	.506* (.153)
Observations	80

The resulting diagram shows the discontinuity of the predicted probabilities at the relative rank of 0. The estimates suggest a positive relationship between the eligibility and the treatment as expected. However, while the predicted probabilities of being treated increases with the relative rank on the left side of the cut-off (at 0), it decreases on the right side of the cut-off.



For estimating the effect of the program at rank = 0 (cut-off = 200, deducted from the actual rank), an instrumental variable (IV) estimation is done taking the actual treatment as the endogenous variable, instrumented by the eligibility based on the rank. The results for a bandwidth of 60 relative ranks is shown below.

	Coefficients and SEs
Actual treatment (=1 if phase I, 0 if in phase II)	70.624 (55.128)
BI rank – cut-off	1.037 (0.0835)
Eligibility* (BI rank – cut-off)	-1.021 (1.106)
Constant	66.039 * (39.829)
Observations	80

The dependent variable is NDVI, measured in April 2007. Being in the phase 1 of NREGS has a positive effect of the vegetation index of a district. This could be the cumulative effect of being in NREGS for a year since NDVI is measured in April 2007, the month when the phase II of the program was introduced. The precision of these estimates is however low.

The next steps in the analysis will be to estimate the effect of the program at the cut-off for other bandwidths, check sensitivity of various covariates to program implementation, compare the results to those obtained from a difference-in-difference estimation, and explore the relationship for more forested districts. NREGS primarily aims to reduce rural poverty. The direct and indirect effects of this program affect natural resource utilization. Our study is a step towards identifying and estimating the impact of this program on vegetation.

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