Public Works, Crowd Out, and Non-Farm Self-Employment: Evidence from India

Preliminary draft. Comments welcome. The latest version can be found here.

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Abstract

Non-farm self-employment plays an important role in the livelihood of rural households in developing countries. However, a growing body of literature suggests that many households enter this sector not for its promise, but rather due to its low entry barriers, which particularly suits poor households coping with shocks, seasonality, and missing markets. If this is true, rising rural wages will likely crowd out households in the sector, causing a decline in the prevalence of non-farm self-employment. In this paper, I use data surrounding the rollout of the Indian Mahatma Gandhi National Rural Employment Guarantee Act to examine the impact of rising rural wages on non-farm self-employment. Consistent with previous research showing that the program increased wages, I find that program rollout induced a large decrease in the prevalence of non-farm self-employment in rural India. The implied labor elasticities in the sector are more than three times higher than economy-wide estimates, suggesting rural non-farm self-employment is a sector of last resort for many individuals. I show that this crowd-out affects the least productive forms of self-employment, as overall average productivity increases following implementation of the program. This conclusion is also borne out at the industry level, as industries with the lowest pre-program wages see the largest decreases in prevalence. Finally, I present evidence that this effect persists even after the program is rolled out throughout the country, suggesting the program induced permanent changes in the rural non-farm self-employment sector. Although crowd-out is often assumed to be an undesirable side effect of government interventions, in the present context it supports the argument that the program is working as intended: the program appears to reduce the reliance on less remunerative forms of employment in rural India.

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1 Introduction

Non-farm self-employment plays an important role in the livelihood of rural households in developing countries.[1] The sector contributes a significant amount of income to rural households (Haggblade et al., 2007) and also plays an important role in risk diversification and consumption smoothing for the poorest households, especially the landless (Reardon et al., 1998). However, a growing body of literature suggests that many households enter this sector not for its promise, but rather due to its low entry barriers, which particularly suits poor households coping with shocks, seasonality, and missing markets (Barrett et al., 2001; Haggblade et al., 2010; Lanjouw and Lanjouw, 2001; Nagler and Naudé, 2014). These households may enter and exit the sector as needed and start enterprises that tend to stay small, offering few prospects for employment generation.

If this perception of non-farm self-employment is true, rising rural wages may crowd out households in the sector, causing a decline in the prevalence of non-farm self-employment. Yet, given the complexity of labor markets, it can be difficult to assess the causal effect of rising wages. In this paper, I use data surrounding the rollout of the Mahatma Gandhi National Rural Employment Guarantee Act (NREGS)[2] to examine the impact of rising rural wages on non-farm self-employment. NREGS is the largest public works — or "workfare" — program in the world, generating more than two billion person-days of employment in 2015/16.[3]

Previous research has found that the program significantly increased prevailing wages in rural areas of India (Azam, 2011; Imbert and Papp, 2015; Deininger et al., 2016). If so,

[1] Throughout this paper, I use the terms "non-farm self-employment"' and "non-farm enterprise" interchangeably.

[2] NREGS was originally passed into law as the National Rural Employment Guarantee Act (NREGA). Its name was later amended to include the name of the Indian independence movement leader. Throughout this paper, I refer to the program as NREGS.

[3] Figures from http://nrega.nic.in/

then the program serves as a plausibly exogenous increase in the prevailing wage rate for individuals in the market and a plausibly exogenous increase in opportunity costs for those out of the market. As such, there are reasons to believe it may crowd out certain types of private-sector employment, especially lower return employment. In this paper, I present evidence of such crowd out.

Using three separate data sources, this paper analyzes the effects of NREGS on the prevalence of non-farm self-employment. I develop a simple model that makes several empirical predictions, all of which are confirmed in the data. I first show that the program has a significant effect on individual non-farm self-employment. The program decreases the probability an individual engages in any non-farm self-employment during the last week by 1.4 percentage points, a more than 10 percent decrease relative to the pre-program mean. In addition, the program decreases days in non-farm self-employment in the last week by 2.7 percent among all adults.

I then show that the program's effects are concentrated in the dry season, consistent with prior evidence (Imbert and Papp, 2015). There is a small and insignificant decrease in days of non-farm self-employment in the rainy season. However, there is a large and statistically significant effect in the dry season: NREGS decreases days of non-farm self-employment by 5.3 percent. A back-of-the-envelope calculation suggests a labor supply elasticity of 1.13, which is more than 3 times as large as estimates of overall labor elasticity (Evenson and Binswanger, 1980; Muralidharan et al., 2017), including estimates calculated using the same data and program as this paper (Imbert and Papp, 2015). This evidence is consistent with non-farm self-employment playing a significant role as a sector of last resort during the dry season.

I present evidence that differences in pre-program trends do not drive the results. Using two waves of NSS data from prior to NREGS implementation as a placebo test, results indi-

cate that trends were plausibly similar; the coefficients in the placebo specifications are less than 15 percent as large as the coefficients in the main specification. In addition, placebo specifications by rainy and dry season show no effects prior to program implementation.

Consistent with the theory, subsequent analyses then show that NREGS had a significant impact on enterprise productivity, measured as revenue per worker-day. This measure of productivity increases by around 35 percent in treated districts relative to untreated districts. In addition, this increase persists even after NREGS is rolled out to the entirety of rural India. This increase in productivity is driven by two separate effects: a "labor substitution" effect, in which households continue to operate their non-farm enterprises but apply less labor to them, and a "composition" effect, in which the least productive enterprises close. While both effects are strong, the composition effect slightly dominates the labor substitution effect.

I explore the types of enterprise that are most likely to close in response to NREGS implementation. First, I present evidence that more prevalent enterprises in the data also tend to have lower wages. This is consistent with self-employment having low capital requirements — and thus low entry barriers — but also low returns (Haggblade et al., 2010). In addition, these are also the enterprises that tend to have the largest change in prevalence by season; two of the most prevalent industries with the lowest wages also show the largest absolute change in prevalence between the rainy and dry seasons. Finally, results show that pre-program industry wages predict the effects of the program on industry prevalence in the dry season, but not in the rainy season. This is again consistent with low return self-employment being more prevalent in the dry season. Moreover, the overall ability of wages to predict program effects persist even five to six years after program implementation.

Finally, credit and savings markets also apparently play an important role in mediating the effects of NREGS on non-farm self-employment. If the increase in wages provides

some households with extra income to overcome entry barriers in more remunerative forms of non-farm self-employment, then households without access to credit are more likely to *increase* non-farm self-employment in response to the program. On the other hand, given prior evidence that savings accounts may be instrumental in helping households overcome limited self-control (Bertrand et al., 2006; Karlan et al., 2009), access to financial institutions may be a prerequisite for many households to enter remunerative forms of non-farm self-employment (Dupas and Robinson, 2013). The data show that households farther from sources that provide both credit and savings see larger decreases in non-farm self-employment than households closer to financial institutions, while households farther from sources of credit alone see slightly smaller decreases, though the latter effect is insignificant. This evidence is consistent with savings accounts—and possible credit—playing an important role in mediating the effects of NREGS on non-farm self-employment. Moreover, this effect is robust to the inclusion of several village-level characteristics that might be responsible for the correlation, including village-level wages, village population, and distance to towns and district headquarters.

This paper contributes to three separate bodies of literature. The first is the growing body of literature on NREGS. A significant portion of this literature examines the labor market impacts of the program, specifically the effect on wages. Much of this literature finds that the program increased prevailing wages in rural areas (Azam, 2011; Imbert and Papp, 2015; Deininger et al., 2016), although the concentration of effects differs, with some authors finding increases mainly in the rainy season (Imbert and Papp, 2015) and others finding an increase in female wages but not male wages (Azam, 2011). On the other hand, Zimmermann (2015) provides evidence the program serves more of a safety net role, and finds few effects on private-sector wages. I add to the NREGS literature by documenting effects on a very specific type of labor: non-farm self-employment.

Second, this paper contributes to the literature on crowd-out of government programs. A long-held view of government-financed job creation was that very little new employment could be created, even in high-unemployment contexts (Peden, 1984). However, more recent evidence from developing countries is somewhat ambiguous, with some studies finding evidence of crowd-out due to government-provided employment, but others finding limited evidence of such an effect (Imbert and Papp, 2015; Zimmermann, 2015). The broader literature on crowding out effects of government spending tends to focus on investment, and the findings are again mixed (Aschauer, 1989; Munnell, 1992; Serven, 1996). This paper suggests large labor-based government programs can indeed crowd out some specific forms on labor.

In addition to employment, a number of studies have examined other examples of crowout due to NREGS. Insofar as wages increased, this may lead to an increase the opportunity costs of time for participants and can therefore have important effects within households. As more adults shift to employment opportunities outside of the household in response to the program, children reallocate their time within the household. One particular consequence of this reallocation of labor is that older children may exit school to take over household tasks — e.g. farming — that used to be performed by adults, decreasing educational attainment among these children (Islam and Sivasankaran, 2014). Shah and Steinberg (2015) present similar findings, showing that NREGA decreases school enrollment as well as some test scores among children aged 13-16.

I find robust evidence that the program led to qualitatively meaningful decreases in nonfarm self-employment, and that these decreases are concentrated in the same season and states as the wage increases. I interpret this as evidence that NREGS crowds out one specific type of private-sector employment. However, while much of the literature implicitly assumes crowd-out is an undesirable side effect of government interventions, this does not

have to be the case. In fact, this paper presents evidence that NREGS may be working as intended: it reduces the reliance on less remunerative forms of employment. In addition, the fact that the effects on non-farm self-employment seem to have some persistence suggests that crowd-out in the sector is not merely accelerating the closure of enterprises that would have failed eventually. Rather, the program seems to be inducing changes that would not have happened on their own, a meaningful finding in the context of public policy evaluation (McKenzie, 2017).

Finally, this paper contributes to the literature on rural non-farm entrepreneurship and self-employment in developing countries. This sector plays an important role for many households, serving as an important source of income (Lanjouw and Shariff, 2004; Lanjouw and Murgai, 2009; Binswanger, 2012) and as a vehicle for risk diversification (Barrett et al., 2001; Kijima and Lanjouw, 2005; Lanjouw and Lanjouw, 2001; Reardon, 1997), especially in areas where income risk from non-farm self-employment is less correlated with agricultural outcomes than other employment options (Dercon, 1996). Despite the importance of the sector for the livelihoods of many households, there is some debate (De Mel et al., 2010) regarding whether individuals engage in non-farm self-employment out of necessity—due to a lack of remunerative employment opportunities (Mead and Liedholm, 1998; Barrett et al., 2001; Schoar, 2010; Cho et al., 2016)—or whether they enter the sector in response to profitable opportunities (Evans and Jovanovic, 1989; Nyshadham, 2013; Falco and Haywood, 2016).

In reality, this dichotomy is likely overly simplistic; households enter the sector for a variety of reasons and in a variety of circumstances. Nonetheless, I find evidence that rural non-farm self-employment may serve as a sector of last resort for at least some households. The estimated labor elasticities during the dry season are more than three times as large as economy-wide labor elasticities for India (Evenson and Binswanger, 1980; Imbert and

Papp, 2015; Muralidharan et al., 2017), indicating non-farm self-employment is more sensitive to wage changes than other sectors. In addition, while pre-program industry wages predict the effects of the program during the dry season, there is no relationship during the rainy season. Overall, the findings suggest many individuals move out of non-farm self-employment following a relatively small increase in the prevailing wage rate and that this exit is concentrated in less remunerative industries.

The rest of this paper is structured as follows. Section 2 provides an overview of the program, including its rollout. Section 3 then presents a simple model of labor allocation for households. Section 4 provides an overview of the data and methodology before Section 5 presents the results. Finally, Section 6 concludes.

2 The National Rural Employment Guarantee Act

Creating employment opportunities and raising wages are key instruments in the fight against poverty (Devereux and Solomon, 2006). While governments use a number of different policies in an attempt to increase employment, perhaps none is as ambitious as India's NREGS. Unlike other workfare programs, NREGS treats employment as a fundamental right, with "workers' rights to demand and get work... enshrined in a legislative framework" (Ministry of Rural Development, 2016, p. 6).

NREGS was originally passed into law as the National Rural Employment Guarantee Act in 2005 (Ministry of Law and Justice, 2005).[4] It is designed as a legal guarantee of employment to households in rural areas. Every rural household is entitled to up to 100 days of manual labor at the statutory minimum wage, which was, on average, approximately 2 USD per day in 2011 (Azam, 2011), although wages vary by state. According to a

[4] All information in this section comes from the original legislation, unless otherwise cited.

presentation from one senior adviser to the government of India,[5] at the start of the program, the official NREGS wage rate varied between 50 rupees (in Gujarat) and 125 rupees (in Kerala). Notably, these official wages often more than doubled the prevailing wage rate at the time for men. For women, the difference was even greater, with the same presentation noting that the prevailing wage rate for women in Rajasthan was only 10 rupees a day prior to implementation of the program, while official NREGS wages were 73 rupees a day. Although the wages were higher than the prevailing wage rates in many states, they are nonetheless designed as a self-targeting mechanism; since the wages are still relatively low, only the poorest households should be interested in applying for jobs through the program (Dutta et al., 2012).

While the program is open to all households in rural areas, interested households must apply for a job card. The job cards are administered by the Gram Panchayat, which is the lowest level of administration in the Indian administrative structure. After receiving a job card, households can apply to the local government for work at any time during the year and must be assigned to a job within 15 days of requesting employment. If applicants do not receive a job within 15 days, they are eligible to receive unemployment compensation — which is equal to between one-fourth and one-half of the official wage rate — until a job is secured. The costs of the program are shared between the federal and state governments, although the federal government bears the majority of costs. The federal government is responsible for all wages of unskilled laborers and three-quarters of all costs for materials as well as skilled and semi-skilled workers. The state government, on the other hand, is responsible for the remaining one-quarter of costs for materials and is completely responsible for unemployment compensation.

A key issue in implementation of the program concerns late payment of wages, which by law must be paid within 15 days. In one study, more than a third of all respondents

[5] http://www.levyinstitute.org/pubs/EFFE/Mehrotra_Rio_May9_08.pdf

reported having to look for work elsewhere due to delays in being paid (Khawlneikim and Mital, 2016), while in another study, every single woman interviewed at worksites in Uttar Pradesh reported wages had not been paid on time (Khera and Nayak, 2009). Insofar as women are more likely to require prompt payment — perhaps because they are the sole wage-earners in the household or they rely on the wages to feed their children — these delays may be leading women to look for opportunities eslewhere (Khera and Nayak, 2009).

Actual implementation of the law took place in three phases. In the first phase, 200 districts received the program in February of 2006. An additional 130 districts received the program between April and May of 2007, while the program was implemented in the remaining districts in April of 2008, bringing the total number of districts with the program to 644 (Ministry of Rural Development, 2013). Figure 1 shows the distribution of districts and phases across India. There is some spatial clustering of phase-one districts — represented by the lightest shade of gray — in the eastern half of country. This is not surprising, as the selection of districts was done based on a number of characteristics, including poverty. According to government documents, the five main variables used to select districts were agricultural productivity per worker, agricultural wage rates, population of scheduled castes and scheduled tribes, agricultural productivity per hectare, and the poverty rate (Planning Commission, 2003). As such, many of the poorest districts were the first to receive the program, and many of these districts are located in the eastern half of the country. It is not clear how this would be correlated with non-farm self-employment, but, given this purposive selection, difference-in-differences estimates — comparing differences in trends — are more likely to provide valid causal inference than a simple comparison of early- and late-phase districts. Nonetheless, given the purposive selection of districts, the parallel trends assumption may be violated. As such, I present evidence In support of this assumption below.

3 The Model

In this section, I develop a simple model and derive three predictions regarding the effects of NREGS on non-farm self-employment. Suppose a single-person household maximizes its utility of consumption and leisure and, for simplicity, assume the household has only three income sources: farm self-employment, non-farm self-employment, and wage employment. In a static framework, the household's problem is:

$$\begin{aligned} & \max_{L_F, L_N, L_w} u(c, l) \\ \text{subject to} \quad & c \leq p_F f(L_F; A) + p_N g(L_N; Z) + w L_w \\ & \bar{L} = L_F + L_N + L_w + l \end{aligned}$$

where c is consumption; p_F is the price of agricultural output; L_F is agricultural labor and $f(L_F; A)$ is the agricultural production function, satisfying $f'(L_F) > 0$ and $f''(L_F) < 0$; A is a measure of capital (e.g. land), assumed to be fixed; p_N is the price of the good produced through non-farm self-employment; L_N is non-farm enterprise labor and $g(L_N; Z)$ is the non-farm production function, satisfying the same assumptions as the agricultural production function; Z is capital used in non-farm production, also assumed to be fixed; w is the wage rate; L_w is amount of wage labor; and $\bar{L}$ is the household's total labor endowment. For simplicity, I assume there is no cap on wage labor.[6]

Assuming an interior solution, the optimal decision is given by:

$$w = p_N g'(L_N) = p_F f'(L_F; A) \tag{1}$$

In other words, the household equates returns to non-farm production — the marginal rev-

[6]All of the results in this section hold with the inclusion of a cap on wage labor.

enue product of labor, or MRPL — with the wage rate. Given the assumptions on the production functions, an increase in the prevailing wage rate will result in a decrease in the amount of labor the household applies to non-farm self-employment, or $\frac{dL_N}{dw} < 0$. The NREGS literature has consistently found that the program increased prevailing wage rates in rural areas. This leads to the first result of the model:

Result 1 *Households will allocate less labor to their non-farm enterprises following implementation of NREGS.*

Two corner solutions are possible with respect to non-farm labor. First, it is possible that some households will prefer to allocate all of their labor to non-farm self-employment. In particular, this will be the case if $p_N g'(\bar{L}) > w$ and $p_N g'(\bar{L}) > p_F f'(0)$.[7] If this is true after implementation of NREGS, then we will see no effect of NREGS on these households. Second, some households may prefer to allocate no labor to non-farm employment. For these households, it must be true that $p_N g'(0) < w$ or $p_N g'(0) < p_F f'(\bar{L})$. This leads to the second prediction of the model:

Result 2 *Fewer households will operate non-farm enterprises following implementation of NREGS.*

Households for which $w_{pre} < p_N f'(0)$ and $\bar{w} > p_N f'(0)$ — where w_{pre} is the prevailing wage rate prior to implementation of NREGS and $\bar{w}$ is the wage rate after implementation — will allocate some positive amount of labor to self-employment prior to NREGS but no labor to self-employment after implementation. This change will appear as a closure of a non-farm enterprise in the data.

The first result also leads to another prediction. If households allocate less labor to non-farm production and the production function is concave, the marginal product of labor

[7] We can also allow for an optimum in which the household allocates labor to both non-farm and farm production, but not wage employment. This will be true if $p_N g'(L_N^*) > w$ and $p_F f'(\bar{L} - L_N^*) > w$.

will increase, or $\frac{dMRPL}{dL_N} < 0$. Since $\frac{dL_N}{dw} < 0$, then, at the new optimum: $\frac{dMRPL}{dw} = \frac{dMRPL}{dL_N}\frac{dL_N}{dw} > 0$. This leads to the final prediction of the model:

Result 3 *The marginal (and average) revenue product of labor will be higher for surviving enterprises following implementation of NREGS.*

It is important to note that Result 3 is really due to two separate effects. First, households will allocate less labor to non-farm production. This suggests that MRPL will be higher in these enterprises following implementation of NREGS, and thus the overall average productivity will be higher. Call this the "labor substitution" effect. Second, Result 2 suggests low productivity enterprises will close completely. This effect will also increase average productivity in NREGS districts. Call this the "composition" effect.

Figure 2 presents graphical examples of the model. In this graphical depiction of the model, I ignore farm labor for simplicity.[8] Given the assumptions on the production function, the MRPL curves will be downward sloping with the shape of the curves in Figure 2. Assuming fixed capital, each row depicts a different possible marginal revenue product of labor curve for a household enterprise. The left column is the household's labor allocation to its non-farm enterprise prior to implementation of NREGS, while the right column is the household's allocation decision following implementation.

Figure 2 presents three separate households. Row A shows a household that is completely unaffected by NREGS. The household's MRPL in non-farm self-employment is high enough that the household will not reallocate any of its labor following the increase in the wage rate. This household's estimated MRPL at the optimum is thus unaffected. Row B shows an example of the labor substitution effect. The household applies labor up to $\bar{L}$ to non-farm self-employment prior to implementation of NREGS, but reduces its allocation of labor to a following implementation. Assuming a concave production function, this im-

[8] As above, the results hold if we redefine the labor endowment in Figure 2 to be non-farm labor.

plies that MRPL at the optimum for household B will increase following implementation.[9] Finally, row C shows a household that is completely crowded out by the program. While the household applies labor up to a to non-farm self-employment prior to the program, the wage change is such that the household applies no labor to non-farm self-employment following implementation. Since the household was less productive — as measured by its MRPL — than household B prior to the program, overall population MRPL will increase when household C reallocates labor. This is the composition effect.

3.1 Choice of Capital and Non-Convexities in Production

The preceding model makes an important assumption: non-farm capital is fixed. If we relax this assumption, comparative statistics can change, especially if we introduce non-convexities. However, a change requires other market failures; if credit and savings markets function well, households will employ an efficient level of capital (Blattman et al., 2013). Without credit and savings markets, households may not be able to overcome entry barriers. Much evidence suggests that credit markets do not function particularly well in developing countries (Blattman et al., 2013; Haushofer and Shapiro, 2016; Bandiera et al., 2017). In addition, without access to savings accounts, many households may fail to save, making short-term decisions that do not align with their long-term interests (Frederick et al., 2002; Blattman et al., 2013). These common market failures result in non-convexities in production that have a number of implications, possibly including poverty traps (Banerjee and Newman, 1993; Aghion and Bolton, 1997; McKenzie and Woodruff, 2006).

The combination of credit/savings market failures and non-convexities—e.g. high start-up costs—may prevent poorer households from engaging in more remunerative non-farm employment. McKenzie and Woodruff (2006) point out three important implications, two

[9]This increase is caused by a shift in labor allocation, not a change in the production function itself.

of which are especially germane to the present discussion. First, the number of firms in the market is not efficient. In particular, there are not enough firms because some would-be entrepreneurs are not able to overcome the start-up costs and thus do not enter the market. Second, entrepreneurs that are able to overcome entry barriers may still not produce at an efficient level if they are not able to invest sufficiently in capital.

These two possibilities present difficulties for the simple model above. We can incorporate non-convexities in production in a simple way, by allowing for two different types of enterprises: a less productive type that requires little to no capital and a more productive type with substantial barriers to entry. This is not unlike some dual-sector models, with a more informal—but less productive—sector acting as a queue for employment in a formal, more productive sector (Harris and Todaro, 1970; Fields, 1975).

The model in the previous section unambiguously predicts a decrease in non-farm self-employment due to an increase in the prevailing wage. However, if the wage change increases household income sufficiently to overcome entry barriers, some households may actually *enter* into non-farm self-employment. In fact, some previous studies have found that the program increased asset accumulation and savings (Deininger and Liu, 2013; Ravi and Engler, 2015; Deininger et al., 2016). On the one hand, this means the theoretical effect of NREGS on non-farm self-employment is ambiguous. On the other hand, it seems unlikely that a wage increase of less than five percent (Imbert and Papp, 2015) would allow a sufficient number of households to overcome startup costs to non-farm self-employment such that the overall effect of NREGS on non-farm self-employment is positive. In the results section, I present estimates that suggest access to savings accounts may be an important predictor of the effects and, thus, that entry barriers may exist to some forms of self-employment. Nonetheless, the main estimates show that the simple model in the previous section explains the overall effects well.

4 Data and Methods

In this paper, I predominately use the Indian National Sample Survey (NSS). The survey is collected on an annual basis by the Ministry of Statistics and Program Implementation. However, not all of the survey rounds are "thick" rounds, with large sample sizes. I use rounds 61 and 64, collected in 2004/05 and 2007/08, respectively, which are the same rounds used by Azam (2011) and Imbert and Papp (2015). The surveys are repeated cross-sections and are representative of the entire population of India. In order to make the results nationally representative, I utilize the NSS survey weights in all of the analyses that follow.

The first round I use comes prior to implementation of the program and the second round comes after the first two phases have been implemented, but prior to implementation of the third phase.[10] Given the timing of the two rounds, I employ a difference-in-differences estimator. I estimate regressions of the form:

$$y_{hdt} = \alpha_d + \beta_1 Post_t + \beta_2 NREGS_d \times Post_t + \phi_{hdt} + \gamma_d \times Post_t + \eta_{st} + \psi_{mt} + \varepsilon_{hdt},$$

where y_{hdt} is the outcome of interest for household h in district d at time t, $Post_t$ is a dummy variable indicating that the observation is from the 2007/08 round, ϕ_{hdt} is a vector of household-level controls, η_{st} is state/wave fixed effects, ψ_{mt} is a vector of dummy variables indicating the month and year of the interview, and ε_{hdt} is a household-specific error term. In addition, all estimates include district-level fixed effects (α_d). All district-level variables are measured prior to the program and are listed in Table A1. I allow these variables to affect the outcome trend by including them as an interaction with the post dummy ($\gamma_d \times Post_t$). I cluster all standard errors at the district level, allowing for arbitrary

[10] Unfortunately, there is no thick round between the first and second phase.

correlation across time (Bertrand et al., 2002).

I use two other data sources. The first is the Additional Rural Incomes Survey/Rural Economic & Demographic Survey, known as ARIS/REDS, which has been collected periodically since 1969.[11] The surveys were originally intended to represent the entire population of India and covered 4,527 households from 259 villages. The two most recent surveys are from 1999 and 2008. The 2008 wave resurveyed all households from 1999 plus approximately eight new households in each village, with a total sample of size of 9,500. Unlike the NSS, the ARIS/REDS contains information on remuneration of non-farm self-employment. I use the ARIS/REDS to examine productivity of non-farm self-employment and the difference-in-differences estimator using the ARIS/REDS identifies the same effect as the NSS as it compares phases one and two to phase three. The ARIS/REDS also has a village-level module that provides information on distance to the nearest bank, which I use to explore effect heterogeneity of NREGS.

The second additional dataset is the India Human Development Survey (IHDS), which is nationally representative and surveyed approximately 42,000 households in 2004-05 and 2011-12.[12] Like the ARIS/REDS, the IHDS contains information on remuneration. I use the IHDS to examine whether NREGS effects dissipate over time.

As with all difference-in-differences estimators, identification relies on the assumption of parallel trends. The assumption is that the trends in outcomes between treatment districts and comparison districts would have been the same in the absence of the program. In practice, this assumption could be violated if, for example, other policies were implemented in only phase one districts between the two survey rounds. I present supporting evidence for the assumption of parallel trends in subsection 5.1.

[11] The survey is organized by the National Council of Applied Economic Research (NCAER). NCAER has collected four rounds between 1971 and 2008. See http://www.ncaer.org/data_details.php?dID=9.

[12] The survey is a joint project of the University of Maryland and the (NCAER) and contains questions on household enterprises. See http://ihds.info/ for more information.

I also estimate robustness checks comparing the effects of NREGS across seasons and states. First, lower-return non-farm self-employment may be more common in the dry season when there are fewer employment options (Barrett et al., 2001; Haggblade et al., 2010; Lanjouw and Lanjouw, 2001; Nagler and Naudé, 2014). In addition, previous NREGS research has found differential effects of the program on wages depending on the season (Imbert and Papp, 2015; Zimmermann, 2012). As such, I analyze the effects of NREGS across the rainy and dry seasons, by estimating separate regressions for each season. In all regressions, the dry season is defined as January through June and the rainy season is defined as July through December.

As an additional check, and again following Imbert and Papp (2015), I create a variable for the "star states" that identifies the best-performing states. These states are Andhra Pradesh, Chhattisgarh, Himachal Pradesh, Madhya Pradesh, Tamil Nadu, Rajasthan, and Uttarakhand. If the effects I find are indeed due to the program, then effects may be concentrated in star states.

4.1 Main Outcomes

NREGS may impact several outcomes related to non-farm self-employment. Most importantly, the program may impact the number of days in non-farm self-employment. The NSS employment module inquires about labor allocation in the last week. Each respondent can report labor allocation in half-day increments. I define self-employment as individuals that responded they either worked in a household enterprises as an own account worker, as an employer, or as an unpaid family worker. In addition, I define non-farm as any industry other than agriculture, livestock, fishing, or mining. Days spent in non-farm self-employment ranges from zero to seven. For the analyses with days below, I use the log of days plus one as the dependent variable. I also present results using levels in the appendix. I

create a second non-farm self-employment variable ("non-farm worker") that equals one if the individual reported spending any time (at least half a day) in non-farm self-employment and zero otherwise. Finally, in the first set of results below, I aggregate responses to the household level, by summing total days (before taking logs) and taking the count and max of non-farm worker.

ARIS/REDS and IHDS allow an examination of the effects of NREGS on non-farm enterprise productivity. Rather than estimating production functions, I define productivity using (log of) average revenue per worker-day.[13] For both the ARIS/REDS and IHDS, I aggregate these variables to the household level.

4.2 Summary Statistics

Table 1 presents (unweighted) district summary statistics by NREGS status. Table A1 in the appendix lists the sources for each of the variables in Table 1. Treated (NREGS) and untreated (non-NREGS) districts appear geographically similar. For example, both types of districts are approximately of the same size in population as well as area. However, other statistics make clear that districts receiving the program first are, on average, poorer and worse off than districts that receive it later. For example, the average wage in NREGS districts was almost 25 percent lower than the wage in non-NREGS districts. This may be partially explained by the composition of the workforce: workers in NREGS districts are more likely to be engaged in agriculture (cultivators and agricultural workers) than workers in non-NREGS districts.

Three other statistics also display the difference in wealth across districts. First, NREGS districts are, on average, much more rural than non-NREGS districts. Second, a higher per-

[13] If production follows a Cobb-Douglas, then the marginal and average products of labor are proportional: $MPL = (1 - \alpha)APL$, where MPL is the marginal product of labor and APL is the average product of labor.

centage of the population of NREGS districts is made up of scheduled tribes and castes—some of the most disadvantaged castes in India—than non-NREGS districts. Finally, the literacy rate is much higher in non-NREGS districts: while more than 58 percent of adults in non-NREGS districts are literate, less than half are literate in NREGS districts. On the whole, these statistics suggest that we must be careful interpreting the results from differences-in-differences, as pre-program trends may be quite different.

Table 2 presents (unweighted) summary statistics at the individual level from the NSS, for individuals between 15 and 60 years of age. Again, we see that the wage was much lower in NREGS districts prior to the program. Regarding the two main outcomes of interest, individuals in NREGS districts are slightly more likely to have worked in non-farm self-employment during the last week. Similarly, they worked, on average, slightly more days in non-farm self-employment than individuals in non-NREGS districts. Many of the other variables do not suggest large differences by district type, except education, which is consistent with the story above and slightly higher in non-NREGS districts.[14]

5 Results

I now turn to results. Table 3 presents the estimated effect of NREGS on non-farm self-employment at the household level. All three coefficients are in the hypothesized direction and are marginally significant or significant (p=0.104, p=0.104, and p=0.089 in columns one, two, and three, respectively). In the data, households decrease their total days of non-farm self-employment by approximately 4.5 percent. In addition, approximately seven percent fewer households operate a non-farm enterprise, relative to the pre-program mean,

[14]Table A4 in the appendix presents unweighted summary statistics for all individuals over the age of ten. The statistics suggest that individuals younger than 15 and older than 60 are much less likely to engage in non-farm self-employment, with the average days in non-farm self-employment almost 20 percent lower than in Table 2. This motivates the restriction of the sample to only individuals between 15 and 60 years of age.

following NREGS implementation.

Table 4 presents results at the individual level. The first column is log of days in self-employment over the last week. We see a decrease in days of non-farm self-employment of approximately 2.7 percent among individuals in NREGS districts relative to individuals in non-NREGS districts. Similarly, treated individuals are 1.4 percentage points less likely to report having worked in non-farm self-employment during the last week. While the coefficient is relatively small, it is nonetheless qualitatively meaningful; it represents an effect more than ten percent as large as the dependent variable mean prior to implementation of the program. Both of the effects in Table 4 are statistically significant.[15]

Interestingly, these effects are not driven only by NREGS employment. Table A3 of the appendix presents results which include days of public works as a covariate. Not surprisingly, the coefficient on public works is negative and highly significant. However, the estimated effects of the program are almost completely unchanged. This suggests that other factors—such as an increasing wage rate—are responsible for the significant shift out of non-farm self-employment, not direct access to NREGS employment.

We might expect the effects of NREGS to differ by season, especially if non-farm self-employment is more or less likely in different seasons or if the wage effect of NREGS shows seasonal variability, as has been found by previous research (Berg et al., 2014; Imbert and Papp, 2015; Deininger et al., 2016). Panel A of Table 5 presents the results disaggregated by season. Column one of Panel A shows no effect of NREGS on non-farm self-employment in the rainy season. However, column two shows a large and highly significant decrease during the dry season. The point estimate indicates that non-farm self-employment decreased by more than five percent in NREGS districts relative to non-

[15]Table A5 in the appendix also presents results for days of non-farm self-employment in levels. The main results are qualitatively unchanged. If anything, the effect of NREGS appears to be larger; the drop in non-farm self-employment overall is more than 12 percent relative to the pre-program mean.

NREGS districts during the dry season, from a pre-program mean of 0.757 days/week. When estimated in levels, the effect is much larger; Appendix Table A5 suggests a drop of more than twenty percent relative to the pre-program mean.

This finding is consistent with non-farm self-employment being less productive during the dry season, which may be indicative of non-farm self-employment being partially a sector of last resort. However, if wages increase more in the dry season than in the rainy season (Imbert and Papp, 2015), sector of last result need not be the explanation. Imbert and Papp (2015), using the same data, find an increase in the wage rate of approximately 4.7 percent and an implied labor elasticity of 0.31. Their estimate of labor elasticity is consistent with both earlier (Evenson and Binswanger, 1980) and later (Muralidharan et al., 2017) estimates for rural India. Using their estimated wage increase of 4.7 percent and the estimated decrease in non-farm self-employment of 5.3 percent in Table 5, the implied labor elasticity is 1.13, much higher than the overall labor elasticity in the economy, even using estimates from the same program and wage increase (Imbert and Papp, 2015). Non-farm self-employment is apparently much more sensitive to wage changes in the dry season than is overall employment, which is consistent with at least part of the sector being subsistence entrepreneurship, or a sector of last resort.

Panel B of Table 5 disaggregates the effect into non-star states and star states (Imbert and Papp, 2015). Consistent with previous evidence, the effect of NREGS on non-farm self-employment is greatest in the states that best implemented the program, the "star states." However, the difference across models is not statistically significant.[16]

Table A6 and Table A7 in the appendix present the individual-level results for all individuals over 10 years of age. The overall effect is smaller in the larger sample, which is not surprising given that the newly included individuals were much less likely to engage in non-

[16] In results not shown but available upon request, I test for significance by completely interacting a star state dummy with all other variables in the model.

farm self-employment prior to implementation of the program (see Table A4). However, effect seasonality is still clear in the more inclusive sample: the largest decrease in non-farm self-employment comes in the dry season. As an additional check, I also re-estimate the overall effect and effects by season using ordered probit, since the labor dependent variable can take on only 15 ordered values at the individual level (zero to seven days in half-day increments). The results in Appendix Table A8 are again qualitatively similar to OLS estimates.

5.1 Pre-Program Trends

While the previous section presented evidence that NREGS decreased the prevalence of non-farm self-employment, the causal interpretation requires an assumption of common trends. To examine the plausibility of this assumption, Figure 3 and Figure 4 graphically present pre-program trends using the 1999/2000 NSS (round 55) and 2004/05 NSS (round 61). Figure 3 presents trends in days of non-farm self-employment.[17] Non-farm self-employment is increasing slightly in both NREGS and non-NREGS districts between 1999/2000 and 2004/05. However, days in non-farm self-employment in treated districts are not rising as quickly as in untreated districts, a finding which might invalidate the causal interpretation above. Figure 4 presents the same trend but using the non-farm worker variable instead of days. The pattern is similar: non-farm self-employment does not appear to be rising as quickly in treated districts as in untreated districts. This overall upward trend is consistent with the non-farm sector helping to absorb an increasing rural labor force (Binswanger, 2012).

While the trend is different in treated districts relative to untreated districts for both days and the non-farm self-employment dummy, the magnitude does not account for the entire

[17] As in the analyses above, the actual variable is log of days plus one.

effect in section 5. To analyze the actual magnitude of these trends, I re-estimate the regressions from Table 4 and Table 5 but use 2004/05 as the "post" wave and 1999/2000 as the pre-program wave. If differential trends are driving the results, then we should see similar results in this placebo analysis. Table 6 presents overall results. After including controls, the trends in both days and the non-farm self-employment dummy are quantitatively small and statistically insignificant. In both columns, the magnitude of the coefficient is less than 15 percent as large as the results in Table 4 and suggest a decrease of less than half of one percent for both variables in the data.

Table 7 presents the placebo test by disaggregating effects by dry/rainy season star/non-star state. Panel A presents results by season. Neither coefficient is significant and the coefficient is actually positive in the dry season. Panel B presents results disaggregate by star state. Both coefficients are statistically significant at the ten-percent level, but the coefficient is actually positive for star states. For non-star states, on the other hand, the negative coefficient is actually around 60 percent as large as the estimated effect from the previous section. This suggests that the difference in the effect across star state status in the previous section may actually be underestimating the true difference. Overall, the placebo results again indicate that failures of the parallel trends assumption are unlikely to be driving the results.

5.2 Enterprise Revenue and Productivity

While the NSS allows an examination of overall employment, it does not allow an examination of the productivity effects of NREGS. As such, I now turn to the two other data sources. Table 8 uses the ARIS/REDS data, at the household level, to look at four separate dependent variables: 1) whether the household engages in non-farm self-employment; 2) the total number of workers employed; 3) total family workers employed; and 4) revenue

per worker-day. Columns one through three confirm the NSS estimates: households are less likely to operate a non-farm enterprise and employ fewer overall workers when they do.

The fourth column is log of revenue per worker-day for only those households that operated a non-farm enterprise. Consistent with the model, the average product of labor (proxied by revenue per worker) apparently increases in NREGS districts relative to non-NREGS districts.[18] This effect is the aggregate of both the labor substitution and composition effects since the estimate incorporates changes in labor supply to enterprises that survive as well as changes in overall industry productivity as less productive enterprises close. Unfortunately, due to sample size, I am not able to disaggregate the two effects.

The second wave of the ARIS/REDS was collected at the same time as the NSS: 2007/08. The second wave of the IHDS, on the other hand, was collected in 2012, after NREGS was implemented in phase three districts.[19] As such, it allows an examination of whether the NREGS effects persist. For example, previous research has found that implementation of welfare programs in India improves with time (Lanjouw and Ravallion, 1999) and, thus, that we might see persistent effects over time. Moreover, since pre-program wages were higher in phase three districts, we might also expect smaller effects in phase three districts, allowing an estimate of some effects even after completion of the roll-out.

Table 9 presents estimates from the IHDS. The dependent variable in the first column is again a simple dummy variable for whether a household operates a non-farm enterprise. Interestingly, the magnitude of the coefficient is almost identical to the coefficient from the NSS results (Table 3). However, it is imprecisely estimated and insignificant at traditional levels. Column two presents the aggregate effect on productivity using revenue per worker-

[18]The model predicted an increase in the marginal product of labor. Assuming Cobb-Douglas production technology, the marginal product of labor is proportional to the average product of labor, and thus changes in the average product will mirror changes in the marginal product.

[19]Recall that there are three separate datasets in this paper: the NSS, the ARIS/REDS, and the IHDS.

day. The estimate is strikingly similar to that using a different dataset at a different time period: the effect of 0.391 in Table 9 is almost identical to the effect of 0.352 in Table 8.

Given the larger sample size, I am also able to estimate the two separate effects directly. Column three presents results for revenue per worker-day for only those households that operated an enterprise in both waves. As such, the coefficient represents the labor substitution effect in the model. The marginally significant (p=0.147) result supports the theoretical model: revenue per worker-day increases in households that operate non-farm enterprises in both waves of the data. Column four, on the other hand, presents results using households that operate a non-farm enterprise in only one wave. This effect represents the composition effect, as enterprises operated only in the first wave are closed at some point between waves while enterprises operated only in the second wave must have been opened. The coefficient of 0.398 against supports the model. Although the difference is not significant, the composition effect is apparently larger than the labor substitution effect in the IHDS data.

5.3 Which Enterprises Close?

The above results support the theoretical model and also suggest that non-farm self-employment may have a relatively large proportion of subsistence enterprises, since workers are most likely to substitute out of these enterprises when other labor opportunities arise. However, to further investigate this possibility, I next present evidence that lower-wage industries see larger effects after NREGS implementation.

Figure 5 presents the industry wage in 2004/05 on the x-axis and the industry prevalence, measured as percent of individuals that worked in that industry, in 2004/05. The NSS does not include data on self-employment income. Thus, it is impossible to construct a measure of income by industry using the NSS. As such, the wages are constructed using casual

workers, not non-farm self-employment workers. The implicit assumption here is that patterns of the overall wages in that industry reflect patterns of self-employment income in that industry, as well. Table A2 in the appendix presents these numbers in table form. There appears to be a relationship between wage and prevalence, with more prevalent industries (e.g. retail trade, clothing manufacturing, and other) also being those with lower wages. This is consistent with households entering less productive industries, which may require less capital and, thus, have lower barriers to entry (Haggblade et al., 2010).

Given that the dry season may make low-return entrepreneurship more likely, we might expect to see differences in industry prevalence across seasons. Figure 6 explores this possibility. Manufacture (clothing) has the lowest average wage in 2004/05, and is on the far left of the figure, while manufacture (wood) as the highest wage and is on the right. The wage is increasing from left to right. Interestingly, clothing manufacturing and retail trade, two industries with the highest prevalence and lowest wages, also show the largest absolute differences in prevalence between the rainy and dry seasons. This is again suggestive of households opening low return enterprises during the dry season.

Given these findings and the fact that NREGS increased wages significantly in the dry season but had no effect in the rainy season, we would expect the effect of NREGS on industry prevalence to be driven by the wage rate prior to its implementation in the dry season but not the rainy season. Figure 7 presents results from a set of regressions. For each industry, a single regression of the effect of NREGS was estimated for both the dry and rainy season. Panel A presents the results for the dry season in graphical form. The individual points indicate the effect for an individual industry, while the line is an OLS line of best fit for the relationship, weighted by initial industry prevalence. In line with expectations, the effect of NREGS on industry prevalence is largest (most negative) for industries that had the lowest wages prior to implementation of the program.[20] In fact, of the six lowest wage

[20]The effect is marginally significant (p=0.105), with standard errors constructed from bootstrapping 1,000

industries, three of them saw the largest effects of the program. Similarly, only three industries saw an increase in prevalence due to the program, two of which had the highest wages prior to implementation. Panel B explores the same relationship during the rainy season. The relationship between initial wage and the effect of NREGS is qualitatively small and in the opposite direction. Overall, Figure 7 presents additional evidence that the effects of NREGS are concentrated in lower return enterprises operated in the dry season.

Finally, I turn to the IHDS to conduct a similar exercise. Recall that the IHDS allows the calculation of actual enterprise returns, since respondents are asked explicitly about revenue from non-farm enterprises. I again use revenue per worker-day as a proxy for productivity. Figure 8 presents results using (log of) revenue per worker-day instead of the wage rate. The results are in line with those from the NSS: the effect is largest on industries with the lowest productivity. Given that the second wave of the IHDS was collected in 2012, the effects of NREGS apparently persist even after implementation of the program in phase three districts, which suggests structural changes to the rural non-farm self-employment sector.

5.4 Effect Heterogeneity

The previous subsections show that the preponderance of evidence suggests that NREGS crowded out a significant portion of non-farm self-employment in rural India. However, the model section also argued that some households might actually be induced to *open* non-farm enterprises in response to the program, especially if the program allowed households to overcome entry barriers by increasing household incomes and/or savings. In this subsection, I present evidence that this effect likely operates in at least some households, though previous results already show that the effect is not large enough to overcome the crowding

replications.

out effect.

Credit and savings market failures may prevent households from entering remunerative forms of non-farm self-employment if there are substantial startup costs. If this is the case, we should see heterogeneity in the effect of NREGS on non-farm self-employment based on access to credit. The ARIS/REDS includes a village-level module with information on distance to the nearest bank. If credit or savings market failures are preventing some households from entering non-farm entrepreneurship, we should see a larger effect of NREGS where these market failures are more likely. In Table 10, I assume being located closer to a financial institution improves access to credit or savings. However, using this variable, the two types of market failures result in opposite predictions. If credit markets are preventing households from entering non-farm self-employment, then (ceteris paribus) households closer to credit should see a more negative effect of NREGS, since the program would be alleviating less of a market failure than for households farther from credit. Households closer to savings accounts, on the other hand, will have a more positive effect of NREGS: the increase in income may allow these households to save more and enter more remunerative forms of non-farm self-employment. Importantly, in Table 10, I use the distance to each financial institution in the pre-NREGS wave.

In all four columns of Table 10, the dependent variable is whether the household operates a non-farm enterprise. The first three columns present results for three financial institutions that provide both credit and savings. In all three cases, the coefficient is negative and significant, suggesting households located farther from a financial institution are more likely to substitute out of non-farm self-employment after the implementation of NREGS. In the fourth column, the financial institution is a money lender. Under the assumption that money lenders provide credit only—and not savings accounts—the marginally significant (p=0.128) positive coefficient is suggestive of credit market failures. Thus, the large

negative coefficients in the first three columns support the hypothesis that NREGS may be increasing savings which can then in turn be used to enter non-farm self-employment and that households without access to savings accounts may be unable to overcome large startup costs.

However, distance to a financial institution may be correlated with other omitted variables that may mediate the effects of NREGS. In particular, distance to a financial institution may be correlated with local wages or distance to other locations, such as large towns or markets. If this is true, then the results in Table 10 may be biased. To alleviate some concerns regarding this possibility, I present further results in Table 11. In the table, the first column replicates the results for the first column in Table 10. The second column adds a control for the local village-level wage in 1999 (prior to NREGS). The third column adds an additional control for village population. The fourth column adds additional controls for distance to the district headquarters as well as distance to the nearest large town. The addition of these controls has little effect on the estimated effect of NREGS by distance to the nearest bank and, if anything, actually increases the coefficient. In the appendix, I present similar results for rural banks, cooperatives, and money lenders in Table A9, Table A10, and Table A11, respectively. The addition of the wage and distances controls does not change any substantive conclusions. Overall, these results are consistent with access to savings accounts, especially, playing an important role in the effects of NREGS on non-farm self-employment.

Another area of interest regards heterogeneity by household and individual characteristics. In particular, heterogeneity may provide some insight into what kinds of individuals work in more remunerative forms of self-employment, which may help provide insight into whether policies designed to encourage entrepreneurship should target certain types of individuals. In particular, I examine heterogeneity by four types of characteristics commonly

cited as correlates of opportunity costs: gender, household size, schooling, and age. In Table 12, I begin with the first three characteristics. Interestingly, only schooling seems to mediate the effects of NREGS. In particular, individuals with higher levels of schooling[21] are more likely to substitute out of non-farm self-employment. This is consistent with two separate stories. First, it may be that individuals prefer wage employment and educated workers are more likely to receive employment on any given day. Second, educated individuals may be more likely to access work through NREGS. However, in the NSS data, individuals with more education actually report fewer hours of public works labor in the previous week (results not shown but available upon request). As such, it appears the first story is more consistent with the data.

The final individual characteristic is age. Since most labor supply variables are quadratic in age, I construct results using separate five-year age groups, starting with 15-20 year olds. I estimate the difference-in-differences specification separately for each age group and present these results graphically in Figure 9. It is difficult to make out a clear pattern, although middle-aged individuals seem to be almost completely unaffected by NREGS. On the other hand, individuals in their 20s seem to be the most likely to substitute out of non-farm self-employment in response to NREGS implementation. However, the effect is also relatively large for individuals over 45. As such, other than education, there do not appear to be clear conclusions regarding their mediation of NREGS effect.

6 Conclusion

In this paper, I present evidence that implementation of the Mahatma Gandhi National Rural Employment Guarantee Act induced significant changes in the rural non-farm self-

[21] The schooling variable is a dummy variable equal to one for literate individuals with at least a primary education.

employment sector. The program led to a decrease in the prevalence of non-farm self-employment at both the household and individual level. Overall, the evidence suggests that the program reduced individuals' reliance on less remunerative forms of non-farm self-employment. In addition, some results support the contention that these effects are not temporary, which would be suggestive evidence that NREGS merely accelerated the closure of household enterprises that were going to fail eventually. Rather, the program apparently induced changes that would not have otherwise occurred, an important finding in its own right (McKenzie, 2017).

Much of the literature on private-sector crowd-out by government programs implicitly assumes that such an effect is an undesirable side effect of government interventions. However, this does not have to be the case. If the program is reducing reliance on less remunerative forms of employment, then we would expect to see an increase in average consumption among households that operate non-farm enterprises, as less productive households exit the sector. Appendix Table A12 presents results using log of per capita consumption as the dependent variable. I do not interpret these regressions as the direct effect of NREGS on consumption; rather, the change is indicative of the sectoral changes brought about by the program. The first column shows that, among households that operated a non-farm enterprise, per capita consumption increased significantly in NREGS districts relative to non-NREGS districts. On the other hand, among households that did not operate a non-farm enterprise, consumption increased insignificantly. In addition, the difference in coefficients across columns is statistically significant (p=0.026; results not shown but available upon request). It appears poorer households in treated districts are less likely to operate a non-farm enterprise in 2007/08 than in 2004/05, relative to untreated districts. It is also these poorest households that are most likely to operate less remunerative forms of non-farm self-employment prior to NREGS. Of course, this evidence is only suggestive; it could be that NREGS increased productivity through its infrastructure investments. However, it is not

clear why these effects would only be seen in the rural non-farm self-employment sector. Rather, these results could be evidence that average consumption of households in the sector increased precisely because NREGS is working: households and individuals apparently exit less remunerative forms of employment for greener pastures.

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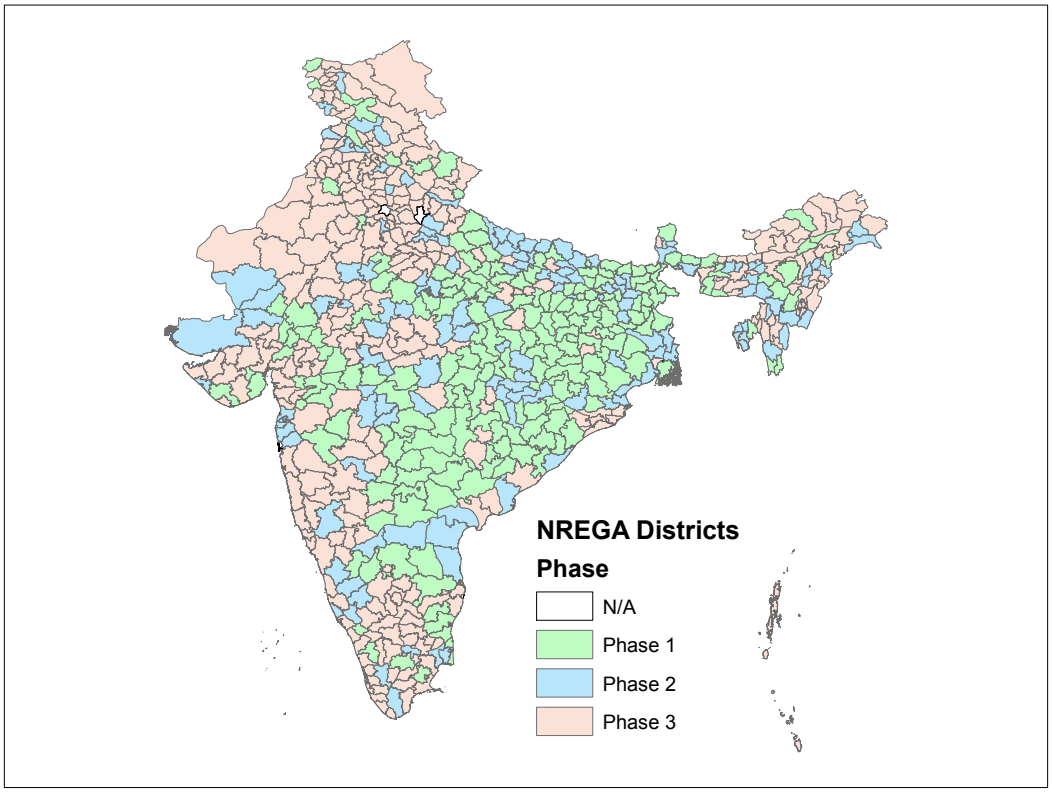
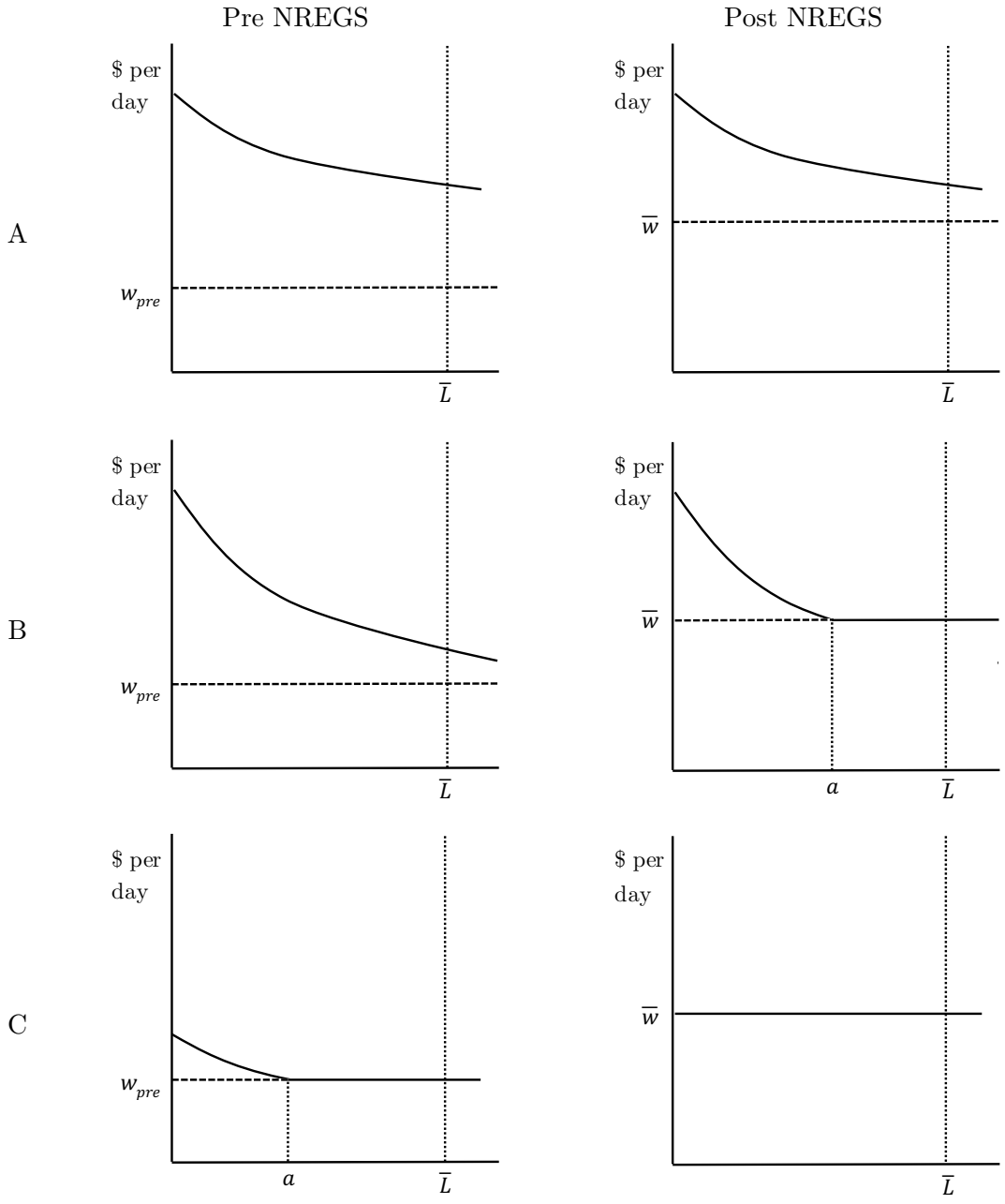
7 Tables

Figure 1: Districts and NREGS Phase



The white-colored districts are either not included in the final NSS sample I use or were ineligible for NREGS.

Figure 2: NREGS and Marginal Revenue Product of Labor



The left column represents non-farm self-employment for three separate example households prior to NREGS implementation. The right column shows the same three households after implementation of NREGS. Row A shows a household that is unaffected by NREGS implementation; MRPL is higher than the post-NREGS wage rate and, as such, the household does not reallocate any labor. Row B shows a household that applies less labor to non-farm self-employment following implementation but continues to operate the non-farm enterprise. Row C shows a household that is completely crowded out of the non-farm self-employment sector by NREGS; the post-NREGS wage rate is high enough that the household allocates no labor to non-farm self-employment following implementation.

Table 1: Summary Statistics - Districts (NSS)

	Pre-Program	
	(1)	(2)
	NREGS	Non-NREGS
Population (thousands)	1749.684	1765.740
	(1354.585)	(1255.065)
Percent rural	0.840	0.716
	(0.112)	(0.168)
Area (km^2)	5958.587	5717.904
	(4659.635)	(5422.598)
Average wage (R's)	49.406	65.297
	(22.912)	(39.717)
Percent scheduled castes	0.145	0.145
	(0.084)	(0.083)
Percent scheduled tribes	0.218	0.114
	(0.271)	(0.244)
Sex ratio	944.562	928.673
	(46.365)	(63.584)
Literacy rate	0.495	0.582
	(0.118)	(0.103)
Labor force participation rate	0.414	0.405
	(0.068)	(0.072)
Cultivators (percent)	0.166	0.150
	(0.084)	(0.095)
Agricultural workers (percent)	0.124	0.076
	(0.062)	(0.051)
Household industry workers (percent)	0.015	0.016
	(0.013)	(0.014)
Other workers (percent)	0.110	0.166
	(0.053)	(0.062)
Observations	288	228

Standard deviations are in parentheses. All statistics are unweighted and are from prior to implementation of NREGS. Table A1 of the appendix details the source for each variable. The first column includes all NREGS districts. The second column includes all non-NREGS districts. Wage is in rupees and is defined as the median wage in 2004/05. The sex ratio is defined as number of females per 1000 males.

Table 2: Summary Statistics - Individual (NSS)

	Pre-Program (2004/05)	
	(1)	(2)
	NREGS	Non-NREGS
Wage (R's)	48.467	63.649
	(25.764)	(43.841)
Non-farm worker (last week - yes=1)	0.141	0.123
	(0.348)	(0.329)
Days non-farm self-employment (last week)	0.762	0.688
	(2.081)	(2.009)
Male	0.503	0.505
	(0.500)	(0.500)
Age	32.482	32.463
	(11.998)	(12.102)
Education	2.275	2.508
	(1.491)	(1.526)
Household head male (yes=1)	0.929	0.920
	(0.257)	(0.271)
Household head age	47.004	48.185
	(12.160)	(12.375)
Household head education	2.148	2.244
	(1.503)	(1.509)
Household size	6.084	6.098
	(3.125)	(2.942)
Percent children	0.281	0.261
	(0.213)	(0.211)
Percent prime male	0.342	0.351
	(0.174)	(0.179)
Percent prime female	0.324	0.329
	(0.145)	(0.148)
Percent elderly female	0.025	0.028
	(0.064)	(0.067)
Observations	120618	91881

Standard deviations are in parentheses. All statistics are unweighted and are from the 2004/05 NSS, which was collected prior to implementation of NREGS. The first column includes all individuals in NREGS districts. The second column includes all individuals in non-NREGS districts. Wage is in rupees. There are 16379 wage observations from NREGS districts and 11514 wage observations from non-NREGS districts. Education is coded from 1-6: 1 indicates less than a primary education; 2 indicates a primary education; 3 indicates a middle-school education; 4 indicates a secondary education; 5 indicates a higher-secondary education; and 6 indicates a college degree. The percent variables following household size are the composition of the individual's household. Children are defined as individuals under 15; prime males are defined as males between 15 and 60 years of age; prime females are defined as females of the same age; and elderly females are defined as females 60 or older.

Table 3: Effect of NREGS on Household Non-Farm Self-Employment

	Household level		
	(1) Self-employment (days - log)	(2) Self-employment (worker count)	(3) NFE HH
Post times NREGS	−0.045	−0.036	−0.020*
	(0.027)	(0.022)	(0.012)
State/Wave	Yes	Yes	Yes
Interview Month/Wave	Yes	Yes	Yes
Observations	141049	141049	141049
DV Mean 2004/05	2.364	0.432	0.288

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the household level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions.. Column one includes total number of days (log + 1) of non-farm self-employment all household members reported engaging in during the previous week. Column two includes total number of household members that reported engaging in any non-farm self-employment during the previous week. The dependent variable in column three equals one if any household member reported engaging in non-farm self-employment during the previous week.

* p<0.1 ** p<0.05 *** p<0.01

Table 4: Effect of NREGS and Individual Non-Farm Self-Employment

	Individual level	
	(1) Self-employment (days - log)	(2) Self-employed (Yes=1)
Post times NREGS	−0.027**	−0.014**
	(0.013)	(0.007)
State/Wave	Yes	Yes
Interview Month/Wave	Yes	Yes
Observations	407553	407553
DV Mean 2004/05	0.233	0.134

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the individual level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions. Column one includes total number of days (log + 1) of non-farm self-employment the individual reported engaging in during the previous week. The dependent variable in column two equals one if the individual reported engaging in any non-farm self-employment during the previous week.

* p<0.1 ** p<0.05 *** p<0.01

Table 5: Effect of NREGS by Season and State

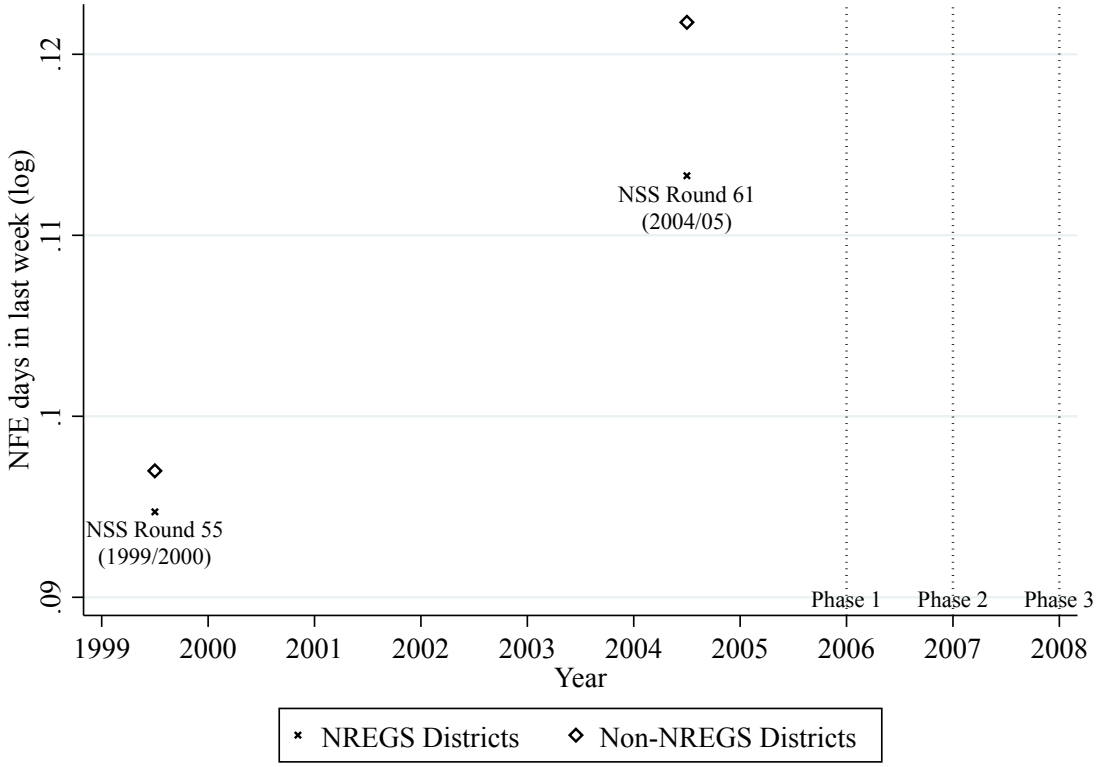
Panel A: Seasons	(1) Rainy Season	(2) Dry Season
Post times NREGS	-0.004	$-0.053***$
	(0.015)	(0.019)
State/Wave	Yes	Yes
Interview Month/Wave	No	No
Observations	203085	204532
DV Mean 2004/05	0.228	0.238

Panel B: Star States	(1) Non-Star States	(2) Star States
Post times NREGS	$-0.022*$	$-0.046*$
	(0.013)	(0.026)
State/Wave	No	No
Interview Month/Wave	Yes	Yes
Observations	101235	306318
DV Mean 2004/05	0.235	0.226

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the individual level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions. In all regressions, the dependent variable is days (log + 1) of non-farm self-employment during the previous week. The top panel reports effects by season. The dry season is defined as January through June while the rainy season is defined as July through December. The bottom panel reports effects by Star state status. Star states are defined as Andhra Pradesh, Chattisgarh, Himachal Pradesh, Madhya Pradesh, Rajasthan, Uttarkhand and Tamil Nadu (Imbert and Papp, 2015).

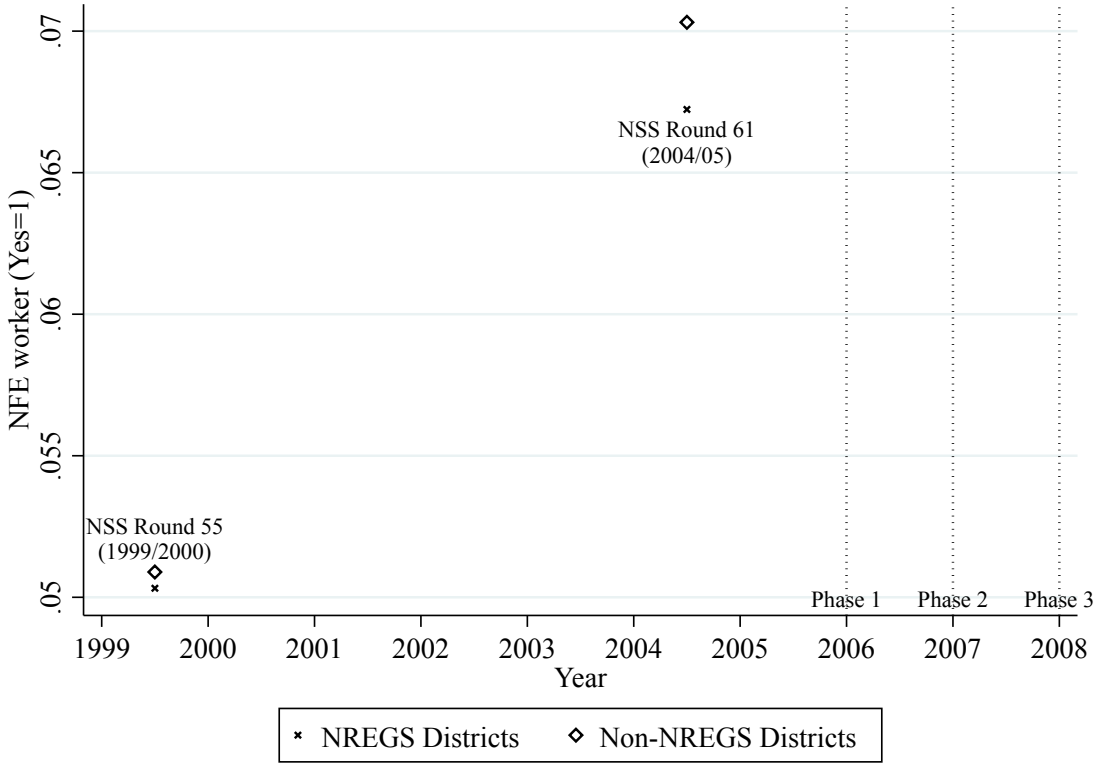
* p<0.1 ** p<0.05 *** p<0.01

Figure 3: Pre-Program Trends in Days of Non-Farm Self-Employment



The y-axis measures average non-farm self-employment days over the last week across individuals in NREGS and non-NREGS districts. All statistics are weighted to be representative of the population.

Figure 4: Pre-Program Trends in Non-Farm Self-Employment



The y-axis measures average non-farm self-employment over the last week across individuals in NREGS and non-NREGS districts. For each individual, non-farm self-employment equals one if they reported engaging in any non-farm self-employment over the last week. All statistics are weighted to be representative of the population.

Table 6: Effect of NREGS on Non-Farm Self-Employment - Placebo

	Individual level	
	(1)	(2)
	Self-employment (days - log)	Self-employed (Yes=1)
Post times NREGS	−0.004	−0.002
	(0.006)	(0.003)
State/Wave	Yes	Yes
Subround/Wave	Yes	Yes
Observations	631788	631788

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the individual level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions. The estimates include the 55th wave of the NSS–collected in 1999/2000–and the 61st wave–collected in 2004/05. Post is now defined as 2004/05, before the program was implemented, in order to assess whether pre-program outcomes are trending differentially. Column one includes total number of days (log + 1) of non-farm self-employment the individual reported engaging in during the previous week. The dependent variable in column two equals one if the individual reported engaging in any non-farm self-employment during the previous week.

* p<0.1 ** p<0.05 *** p<0.01

Table 7: Effect of NREGS by Season and State - Placebo

	(1)	(2)
Panel A: Seasons	Rainy Season	Dry Season
Post times NREGS	−0.010	0.001
	(0.008)	(0.010)
State/Wave	Yes	Yes
Subround/Wave	No	No
Observations	317269	314519

	(1)	(2)
Panel B: Star States	Non-Star States	Star States
Post times NREGS	−0.013*	0.018*
	(0.007)	(0.010)
State/Wave	No	No
Subround/Wave	Yes	Yes
Observations	476905	154883

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the individual level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions. The estimates include the 55th wave of the NSS–collected in 1999/2000–and the 61st wave–collected in 2004/05. Post is now defined as 2004/05, before the program was implemented, in order to assess whether pre-program outcomes are trending differentially. In all regressions, the dependent variable is days (log + 1) of non-farm self-employment during the previous week. The top panel reports effects by season. The dry season is defined as January through June while the rainy season is defined as July through December. The bottom panel reports effects by star state status. Star states are defined as Andhra Pradesh, Chattisgarh, Himachal Pradesh, Madhya Pradesh, Rajasthan, Uttarkhand and Tamil Nadu (Imbert and Papp, 2015).

* p<0.1 ** p<0.05 *** p<0.01

Table 8: Effect of NREGS on Non-Farm Self-Employment Income - ARIS/REDS

	All	NFE Households		
	(1)	(2)	(3)	(4)
	NFE HH	Workers (log)	Family Workers (log)	Rev. per Worker-Day
Post times NREGS	−0.058*	−0.124*	−0.157*	0.352**
	(0.034)	(0.071)	(0.083)	(0.146)
State/Wave	Yes	Yes	Yes	Yes
Observations	8231	1018	1018	993

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the household level. All regressions use the ARIS/REDS. Due to sample size, district fixed effects are not included in the estimation. The first column includes households. The dependent variable in the first column is a dummy variable equal to one if the household operated a non-farm enterprise of any type. The second through fourth columns include only households that operated a non-farm enterprise. The dependent variable in the second column is (log of) number of total workers. The dependent variable in the third column is (log of) number of family workers. The dependent variable in the fourth column is (log of) revenue per worker-day.

* p<0.1 ** p<0.05 *** p<0.01

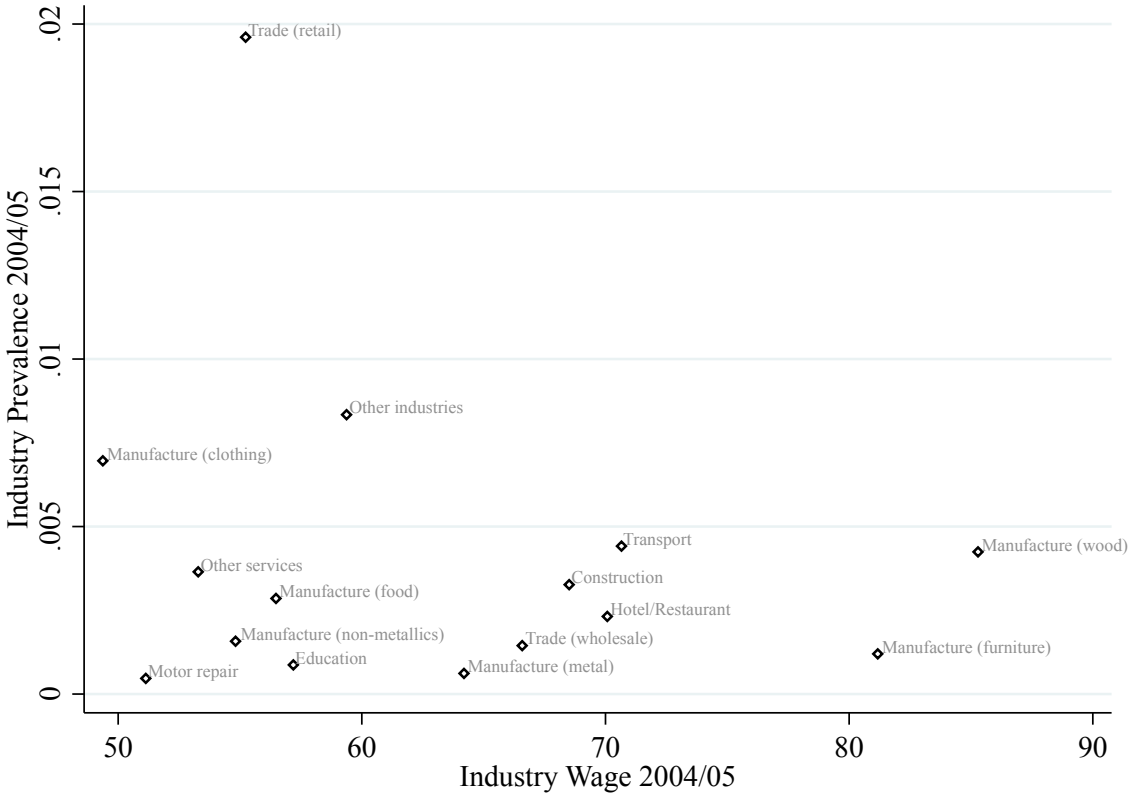
Table 9: Effect of NREGS on Non-Farm Self-Employment Income - IHDS

	All Households	NFE Households - RPD (log)		
	(1)	(2)	(3)	(4)
	NFE HH	All	In Both Waves	In One Wave
Post times NREGS	−0.020	0.391**	0.277	0.398*
	(0.016)	(0.194)	(0.190)	(0.225)
Observations	46097	4959	2122	2837

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the household level. All regressions use the IHDS. Regressions are weighted to be representative of the population. District fixed effects are included in all regressions. The first column includes households. The dependent variable in the first column is a dummy variable equal to one if the household operated a non-farm enterprise of any type. The dependent variable of the second, third, and fourth columns is (log of) revenue per worker-day (RPD). The second column includes all households with at least one non-farm enterprise. The third column includes only households that operated at least one non-farm enterprise in both waves. The fourth column includes only households that operated a non-farm enterprise in only one wave.

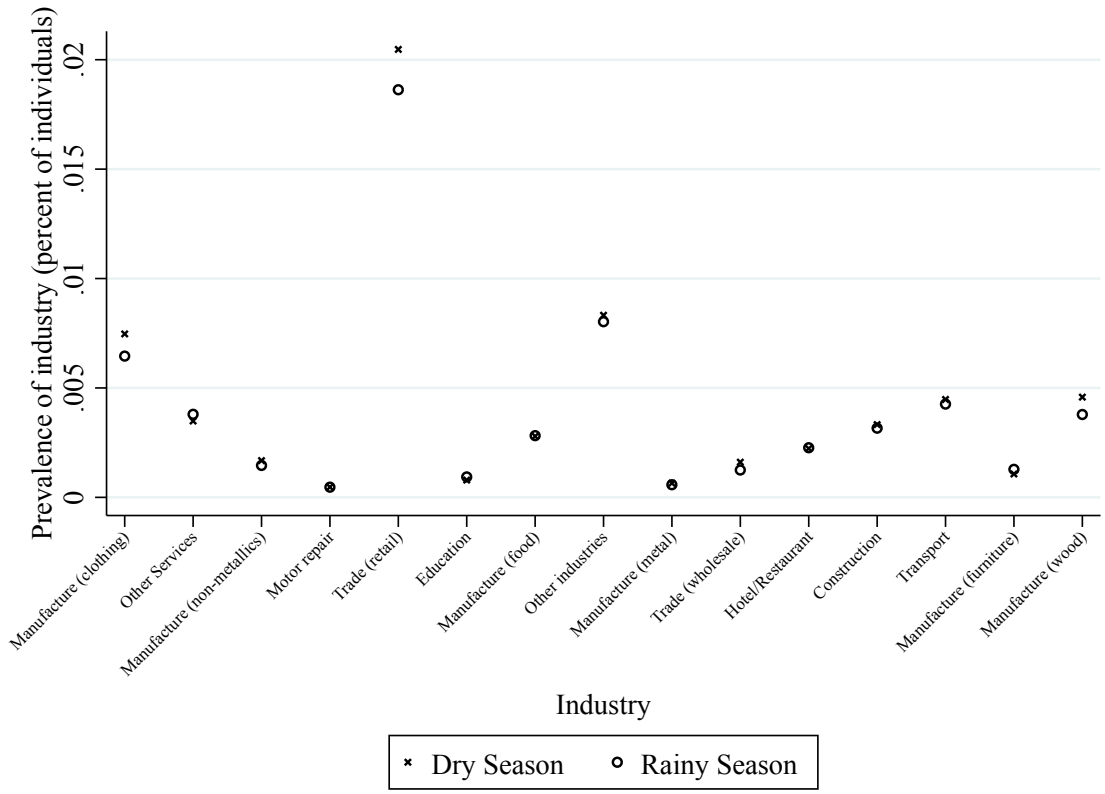
* p<0.1 ** p<0.05 *** p<0.01

Figure 5: Industry Prevalence and Wages - 2004/05



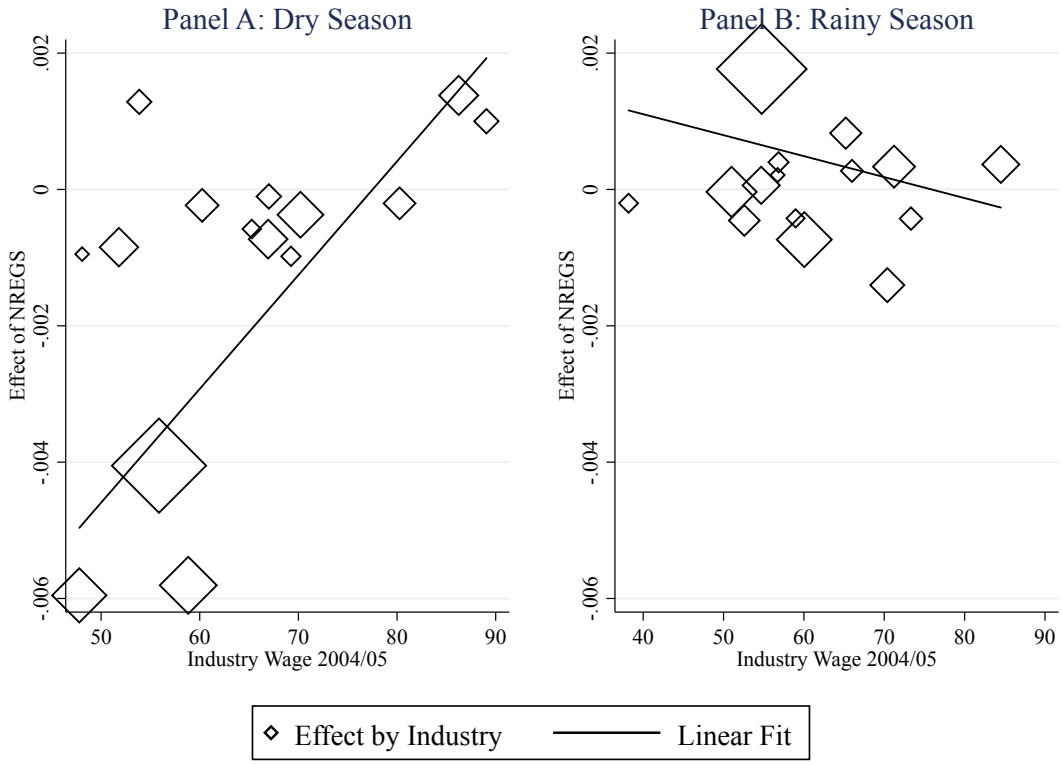
The x-axis represents the industry-level wage in 2004/05. The wage is constructed using casual wages–not self-employment income–since individuals engaged in non-farm self-employment do not report earnings in the NSS. The y-axis represents the prevalence of each industry in 2004/05. The prevalence is defined as the percentage of individuals that reported any self-employment in the industry. Both wages and prevalence are weighted to be representative of the population.

Figure 6: Industry Prevalence by Season - 2004/05



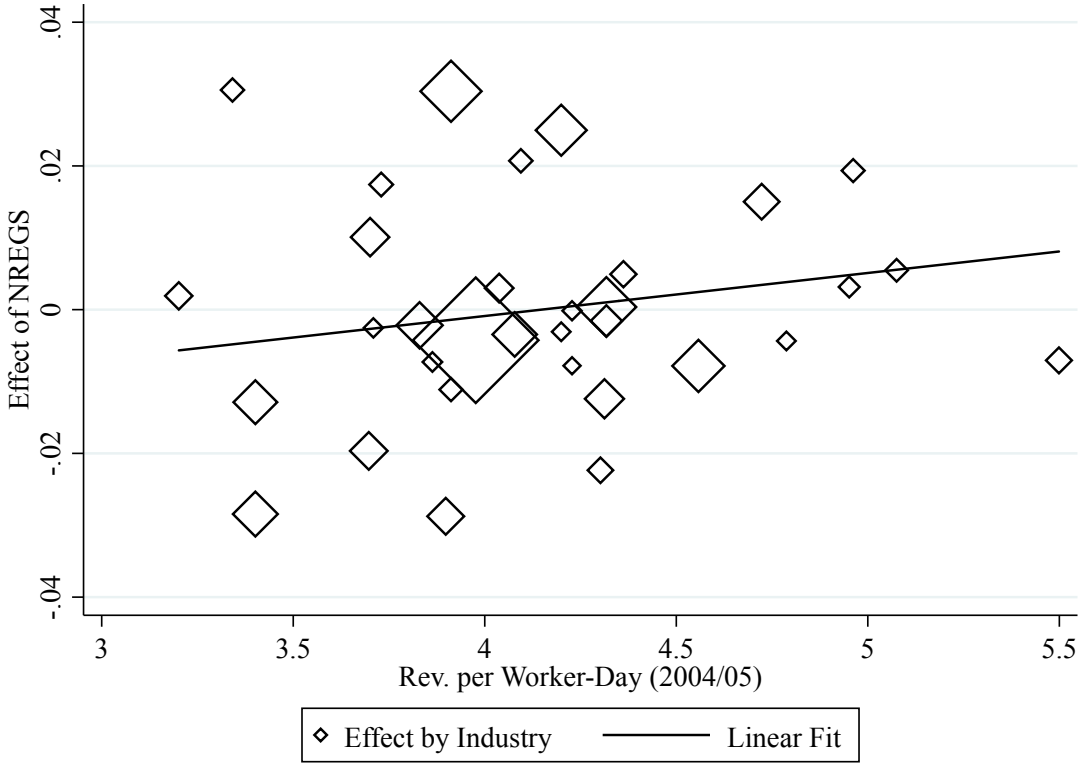
The y-axis represents the prevalence of each industry in 2004/05. The dry season is defined as January through June and the rainy season is defined as July through December. The prevalence is defined as the percentage of individuals that reported any self-employment in the industry. Statistics are weighted to be representative of the population.

Figure 7: Effect of NREGS by Industry Wage



In both panels, the y-axis represents the effect of NREGS on industry prevalence. The x-axis represents the overall industry wage in 2004/05, for the relevant season, prior to NREGS implementation. The dry season is defined as January through June and the rainy season is defined as July through December. The prevalence is defined as the percentage of individuals that reported any self-employment in the industry. The estimates are weighted to be representative of the population. In addition, the linear fit and the figure are weighted by pre-NREGS industry prevalence.

Figure 8: Effect of NREGS by Industry Productivity



In both panels, the y-axis represents the effect of NREGS on industry prevalence. Since the estimation is at the non-farm enterprise level, prevalence is defined relative to other non-farm enterprises, not in the population as a whole. The x-axis represents the overall industry revenue per worker-day in 2004/05, for only households that did not hire any workers, prior to NREGS implementation. Estimation is restricted to only households that did not hire any workers due to data limitations. Statistics are weighted to be representative of the population. In addition, the linear fit and the figure are weighted by pre-NREGS industry prevalence.

Table 10: Effect of NREGS and Access to Financial Institutions

	(1) Bank	(2) Rural Bank	(3) Cooperative	(4) Money Lender
Post times NREGS times Distance (log)	−0.054*	−0.103***	−0.055*	0.029
to Financial Institution	(0.030)	(0.030)	(0.029)	(0.019)
State/Wave	Yes	Yes	Yes	Yes
Observations	8231	8231	8231	8231

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the household level. All regressions use the ARIS/REDS. Due to sample size, district fixed effects are not included in the estimation. The financial institution in the first through fourth columns are a bank, rural bank, cooperative, and money lender, respectively. Distances are defined from the enumerated village.

* p<0.1 ** p<0.05 *** p<0.01

Table 11: Effect of NREGS and Rural Banking

	(1) NFE HH	(2) NFE HH	(3) NFE HH	(4) NFE HH
Post times NREGS times Distance (log) to Bank	−0.054*	−0.068**	−0.063**	−0.063**
	(0.030)	(0.031)	(0.031)	(0.031)
State/Wave	Yes	Yes	Yes	Yes
Village Wage (1999)	No	Yes	Yes	Yes
Village Population	No	No	Yes	Yes
Village Distance Variables	No	No	No	Yes
Observations	8231	8132	7889	7889

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the household level. All regressions use the ARIS/REDS. Due to sample size, district fixed effects are not included in the estimation. The dependent variable in all columns is an indicator for whether the household operated a non-farm enterprise or not. Distances are defined from the enumerated village. "Village Distance Variables" include distance to nearest town and distance to the district headquarters.

* p<0.1 ** p<0.05 *** p<0.01

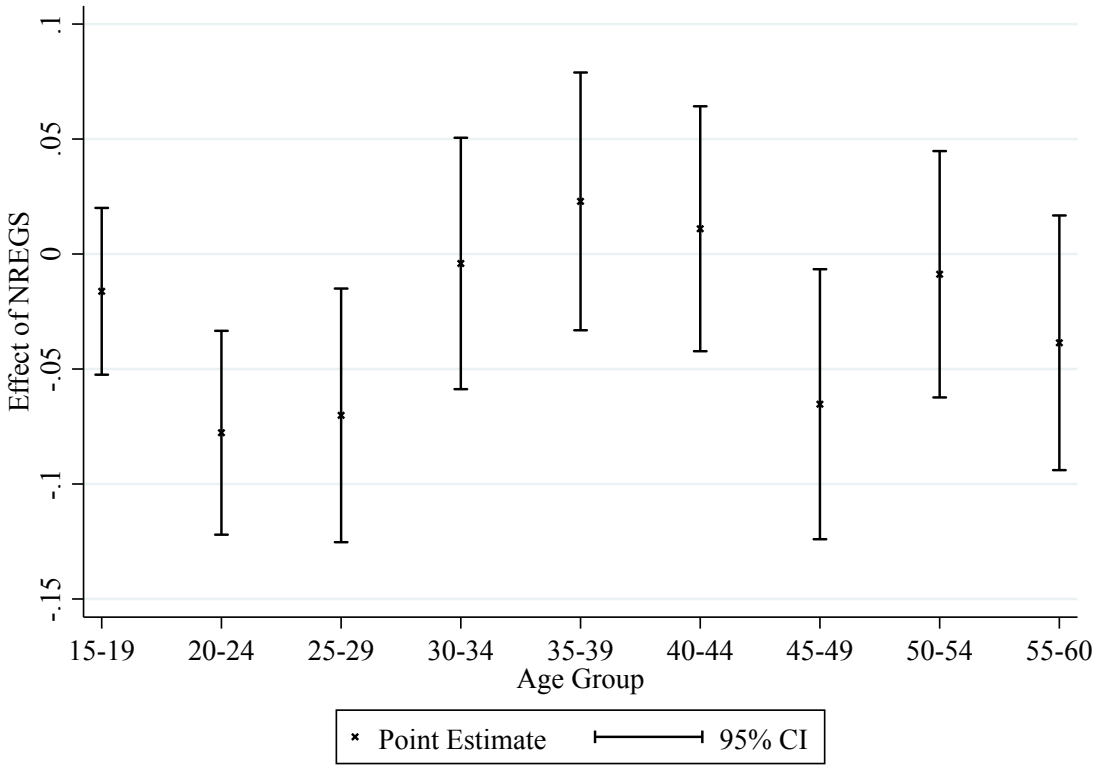
Table 12: Effect of NREGS by Individual Characteristics

	(1) Male	(2) HH Size	(3) Schooling
Post times NREGS times Male	0.002		
	(0.017)		
Post times NREGS times Household Size		0.003	
		(0.020)	
Post times NREGS times Schooling			−0.025*
			(0.014)
State/Wave	Yes	Yes	Yes
Interview Month/Wave	Yes	Yes	Yes
N	407553	407553	407369

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the individual level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions. Each column presents results from a different regression, including a triple interaction to examine whether the effect of NREGS on non-farm self-employment varies with individual characteristics. The schooling variable is a dummy variable equal to one if the individual has at least a primary school education.

* p<0.1 ** p<0.05 *** p<0.01

Figure 9: Effect of NREGS by Age



The graph shows the change in the effect of age on non-farm self-employment for NREGS districts (solid line) and non-NREGS districts (dashed line). It also shows the difference-in-differences effect (dotted line).

Appendix

Table A1: District-Level Controls

Variable	Source
Population	2001 Census
Percent rural	2001 Census
Area	2001 Census
Casual wage	2004/05 NSS
Percent scheduled castes	2001 Census
Percent scheduled tribes	2001 Census
Sex ratio	2001 Census
Literacy rate	2001 Census
Labor force participation rate	2001 Census
Labor force composition	2001 Census
Rainfall for previous year	University of East Anglia[1]
Rainfall for current year	University of East Anglia

[1] http://www.cru.uea.ac.uk/data

Table A2: Summary Statistics - Non-Farm Self-Employment Industries

	Pre-Program (2004/05)	
	Operation (Yes=1)	Wage (Rupees)
Manufacturing (wood)	0.004	85.289
Manufacturing (furniture)	0.001	81.175
Transport	0.004	70.657
Hotel and restaurant	0.002	70.075
Construction	0.003	68.511
Trade (wholesale)	0.001	66.583
Manufacturing (metal)	0.001	64.194
Other industries	0.008	59.375
Education	0.001	57.191
Manufacturing (food)	0.003	56.479
Trade (retail)	0.020	55.233
Manufacturing (non-metallic)	0.002	54.819
Other services	0.004	53.286
Motor vehicle repair	0.000	51.136
Manufacturing (clothing)	0.007	49.374
All industries	0.069	65.125
Observations	398006	

All statistics are weighted and are from the 2004/05 NSS, which was collected prior to implementation of NREGS. The first column shows the prevalence of each industry. For example, 0.4 percent of individuals reported engaging in manufacturing (wood) as non-farm self-employment. The second column is mean wage for each industry. However, wages are defined for all workers in the industry, since those individuals reporting non-farm self-employment do not report earnings in the NSS.

Table A3: Effect of NREGS - Public Works Days as Covariate

	Individual level	
	(1)	(2)
	Self-emp (log days)	Self-emp (Yes=1)
Post times NREGS	−0.026*	−0.013*
	(0.014)	(0.008)
Days of Public Works (log)	−0.096***	−0.043***
	(0.006)	(0.004)
State/Wave	Yes	Yes
Interview Month/Wave	Yes	Yes
Observations	407553	407553
DV Mean 2004/05	0.233	0.134

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the individual level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions. Individuals between 15 and 60 years of age are included in estimation. Column one includes total number of days (log + 1) of non-farm self-employment the individual reported engaging in during the previous week. The dependent variable in column two equals one if the individual reported engaging in any non-farm self-employment during the previous week. In both regressions, log of days of public works is included as a covariate.

* p<0.1 ** p<0.05 *** p<0.01

Table A4: Summary Statistics - All Individuals over Ten

	Pre-Program (2004/05)	
	(1)	(2)
	NREGS	Non-NREGS
Wage (R's)	47.907	63.136
	(25.675)	(43.546)
Non-farm worker (last week - yes=1)	0.115	0.101
	(0.319)	(0.301)
Days non-farm self-employment (last week)	0.622	0.561
	(1.904)	(1.833)
Male	0.507	0.509
	(0.500)	(0.500)
Age	32.474	32.989
	(16.977)	(17.403)
Education	2.106	2.294
	(1.391)	(1.438)
Household head male (yes=1)	0.925	0.917
	(0.263)	(0.276)
Household head age	47.812	49.040
	(12.702)	(13.030)
Household head education	2.121	2.208
	(1.491)	(1.497)
Household size	6.150	6.154
	(3.154)	(2.966)
Percent children	0.304	0.285
	(0.216)	(0.214)
Percent prime male	0.314	0.320
	(0.173)	(0.178)
Percent prime female	0.304	0.307
	(0.145)	(0.148)
Percent elderly female	0.039	0.044
	(0.098)	(0.102)
Observations	159710	122403

Standard deviations are in parentheses. All statistics are unweighted and are from the 2004/05 NSS, which was collected prior to implementation of NREGS. The first column includes all individuals in NREGS districts. The second column includes all individuals in non-NREGS districts. Wage is in rupees. Education is coded from 1-6: 1 indicates less than a primary education; 2 indicates a primary education; 3 indicates a middle-school education; 4 indicates a secondary education; 5 indicates a higher-secondary education; and 6 indicates a college degree. The percent variables following household size are the composition of the individual's household. Children are defined as individuals under 15; prime males are defined as males between 15 and 60 years of age; prime females are defined as females of the same age; and elderly females are defined as females 60 or older. All individuals over ten years of age are included in the statistics.

Table A5: Effect of NREGS on Days of Non-Farm Self-Employment - Levels

		By Season	
	(1)	(2)	(3)
	All	Dry	Rainy
Post times NREGS	−0.086*	−0.189***	0.016
	(0.047)	(0.065)	(0.056)
State/Wave	Yes	Yes	Yes
Interview Month/Wave	Yes	No	No
Observations	407553	203085	204532
DV Mean 2004/05	0.737	0.757	0.717

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the individual level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions. Individuals between 15 and 60 years of age are included in estimation. The dependent variable in all columns is the number of days of non-farm self-employment (in levels).

* p<0.1 ** p<0.05 *** p<0.01

Table A6: Effect of NREGS on Non-Farm Self-Employment - All Individuals over Ten

	Individual level	
	(1)	(2)
	Self-emp (log days)	Self-emp (Yes=1)
Post times NREGS	−0.020*	−0.010
	(0.011)	(0.006)
State/Wave	Yes	Yes
Interview Month/Wave	Yes	Yes
Observations	539813	539813
DV Mean 2004/05	0.190	0.110

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the individual level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions. All individuals over ten years of age are included in estimation. Column one includes total number of days (log + 1) of non-farm self-employment the individual reported engaging in during the previous week. The dependent variable in column two equals one if the individual reported engaging in any non-farm self-employment during the previous week.

* p<0.1 ** p<0.05 *** p<0.01

Table A7: Effect of NREGS by Season - All Individuals over Ten

	(1) Dry Season	(2) Rainy Season
Post times NREGS	-0.043***	0.002
	(0.016)	(0.014)
State/Wave	Yes	Yes
Observations	268672	271217
DV Mean 2004/05	0.194	0.185

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the individual level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions. All individuals over ten years of age are included in estimation. Column one includes total number of days (log + 1) of non-farm self-employment the individual reported engaging in during the previous week. The dependent variable in column two equals one if the individual reported engaging in any non-farm self-employment during the previous week.

* p<0.1 ** p<0.05 *** p<0.01

Table A8: Effect of NREGS on Non-Farm Self-Employment - Ordered Probit

		By Season	
	(1) All	(2) Dry	(3) Rainy
Post times NREGS	-0.117**	-0.228***	0.017
	(0.052)	(0.073)	(0.064)
State/Wave	Yes	Yes	Yes
Interview Month/Wave	Yes	No	No
Observations	407553	203085	204532

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the individual level. All regressions use the NSS and are weighted to be representative of the population. District fixed effects are included in all regressions. Individuals between 15 and 60 years of age are included in estimation. The dependent variable in all columns is the number of days of non-farm self-employment and takes on 15 possible values from zero to seven days in half-day increments. All results are estimated using ordered probit.

* p<0.1 ** p<0.05 *** p<0.01

Table A9: NREGS and Rural Banks

	(1) NFE HH	(2) NFE HH	(3) NFE HH	(4) NFE HH
Post times NREGS times Distance (log)	−0.103***	−0.091**	−0.090**	−0.090**
to Rural Bank	(0.030)	(0.037)	(0.038)	(0.039)
State/Wave	Yes	Yes	Yes	Yes
Village Wage (1999)	No	Yes	Yes	Yes
Village Population	No	No	Yes	Yes
Village Distance Variables	No	No	No	Yes
Observations	8231	8132	7889	7889

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the household level. All regressions use the ARIS/REDS. Due to sample size, district fixed effects are not included in the estimation. The dependent variable in all columns is an indicator for whether the household operated a non-farm enterprise or not.

* p<0.1 ** p<0.05 *** p<0.01

Table A10: NREGS and Cooperatives

	(1) NFE HH	(2) NFE HH	(3) NFE HH	(4) NFE HH
Post times NREGS times Distance (log)	−0.055*	−0.054*	−0.053	−0.056*
to Cooperative	(0.029)	(0.032)	(0.032)	(0.034)
State/Wave	Yes	Yes	Yes	Yes
Village Wage (1999)	No	Yes	Yes	Yes
Village Population	No	No	Yes	Yes
Village Distance Variables	No	No	No	Yes
Observations	8231	8132	7889	7889

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the household level. All regressions use the ARIS/REDS. Due to sample size, district fixed effects are not included in the estimation. The dependent variable in all columns is an indicator for whether the household operated a non-farm enterprise or not.

* p<0.1 ** p<0.05 *** p<0.01

Table A11: NREGS and Money Lenders

	(1) NFE HH	(2) NFE HH	(3) NFE HH	(4) NFE HH
Post times NREGS times Distance (log)	0.029	0.019	0.019	0.020
to Money Lender	(0.019)	(0.016)	(0.017)	(0.017)
State/Wave	Yes	Yes	Yes	Yes
Village Wage (1999)	No	Yes	Yes	Yes
Village Population	No	No	Yes	Yes
Village Distance Variables	No	No	No	Yes
Observations	8231	8132	7889	7889

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the household level. All regressions use the ARIS/REDS. Due to sample size, district fixed effects are not included in the estimation. The dependent variable in all columns is an indicator for whether the household operated a non-farm enterprise or not.

* p<0.1 ** p<0.05 *** p<0.01

Table A12: NREGS, NFEs, and Consumption

	(1) NFE HH	(2) Non-NFE HH
Post times NREGS	0.342**	0.073
	(0.146)	(0.111)
State/Wave	Yes	Yes
Observations	1018	7213

Standard errors are in parentheses and clustered at the district level. All regressions are defined at the household level. All regressions use the ARIS/REDS. Due to sample size, district fixed effects are not included in the estimation. The first column includes households that operate a non-farm enterprise. The second column includes households that do not operate a non-farm enterprise. The dependent variable in both columns is log of per capital consumption (R's).

* p<0.1 ** p<0.05 *** p<0.01