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An employment guarantee as risk insurance? Assessing the effects of the NREGS on agricultural production decisions

Esther Gehrke*

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Abstract

This paper assesses the role of risk constraints in households' production decisions. Using representative panel data for Andhra Pradesh, India, it analyses the effects of the National Rural Employment Guarantee Scheme (NREGS) on households' crop choices. This paper shows that the introduction of the NREGS reduces households' uncertainty about future income streams because it provides reliable employment opportunities in rural areas independently of weather shocks and crop failure. Households with access to the NREGS can therefore increase the share of inputs allocated to more profitable but also riskier crops, especially cotton. These shifts in agricultural production can considerably raise the incomes of smallholder farmers. Linking the employment guarantee to risk considerations is the key innovation of this paper. Therewith, it provides empirical evidence of the validity of the theory of decision-making under uncertainty and contributes to the ongoing debate on the effects of the NREGS on agricultural productivity.

Keywords: Uncertainty; Employment Guarantee; Crop choice
JEL: I38; O12; Q16

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1 Introduction

Previous research suggests that farmers in developing countries are constrained in their production and investment decisions. Evidence of delayed technology adoption, low investment in fixed capital, a preference for conservative crop choices and, more generally, a lack of innovative capacity is by now well established (Foster and Rosenzweig, 2010; Duflo et al., 2008; Suri, 2011). This has potentially severe and long-lasting effects on income and well-being in developing countries as a large share of their populations still rely on agricultural production as a major source of income.

Empirical evidence points to different explanations for the low propensity to innovate. Learning processes have been shown to discourage technology adoption (Besley and Case, 1993; Munshi, 2004; Conley and Udry, 2010), as have time-inconsistent preferences (Duflo et al., 2011) and low levels of human capital (Foster and Rosenzweig, 1996). In addition, market imperfections such as the lack of insurance mechanisms, dysfunctional labour markets and limited access to credit are often cited explanations. On the relative importance of these constraints, however, the literature is much less conclusive. Rosenzweig and Binswanger (1993) and Dercon (1996) provide evidence that uninsured risks prevent farmers from holding profitable asset portfolios and planting profitable crops. On the other hand, Rosenzweig and Wolpin (1993), Fafchamps and Pender (1997) and Gine and Klonner (2005) identify the lack of credit as a major explanation for foregone profits. One of the major challenges in disentangling both constraints is to find exogenous variation in one or both. Observational studies mainly rely on proxies for both constraints, but face the challenge that indicators representing a household's ability to cope with shocks (such as wealth, human or social capital) are typically the same indicators that predict access to credit and or own financing possibilities.

More recent literature has made important progress in dealing with these methodological challenges. Dercon and Christiaensen (2011), for example, assess the relative importance of risk versus credit constraints by constructing an indicator of household risk exposure that combines a household's probability of facing a rainfall shock with its ability to cope with such a shock. They thereby circumvent the attribution problem of using only wealth as a proxy for a household's capacity to smooth consumption. The authors show that Ethiopian households with lower expected consumption outcomes - due to high risk exposure and low savings - are less likely to invest in fertilizer. Other authors have used randomized variation in the availability of insurance mechanisms and/or access to finance to estimate the relative importance of each of the interventions. These articles find that crop insurance is critical in stimulating fertilizer application (Karlan et al., 2012) and risky crop choice (Cole et al., 2013). Karlan et al. (2012) also found that uninsured risk is a more important determinant of low investment rates than are constraints in access to capital.

This paper aims at contributing to the empirical evidence on the importance of risk constraints in farmers' production decisions. But instead of exploring variance in the availability of insurance, as do the studies cited above, it examines variation in the access to an alternative mechanism that could improve a household's risk management:

an employment guarantee. The main argument is that public works programmes or employment guarantees could help households to cope with income shocks by providing additional employment opportunities. This idea is not new; the potential of public works schemes in helping households to smooth income in the case of shocks has been highlighted *inter alia* by Barrett et al. (2005) and Binswanger-Mkhize (2012). However, to the best of my knowledge, no empirical evidence on the insurance effect of an employment guarantee on households' production decisions has been provided so far.

In this paper I test the extent to which the introduction of the National Rural Employment Guarantee Scheme (NREGS) reduces households' uncertainty about future income streams and enables them to produce a higher share of high-risk, high-profit crops. The National Rural Employment Guarantee Act (NREGA) was passed in India in September 2005; the implementation thereof began in 2006. The NREGA entitles every rural household to up to a 100 days of work per year at the state minimum wage, which is to be provided by the block officer within 14 days of the application for work being made.[1] Today the NREGS is the largest public works programme in the world. In the financial year 2010/11 it provided work to close to 55 million rural households (MoRD-GoI 2012). A total of 2.5 billion person-days of employment were generated in the same year.

The question outlined above is tested using a household-level panel data set that is representative of the state of Andhra Pradesh in southern India. The quality of implementation of the NREGS has been shown to vary immensely across India (Dutta et al., 2012). In most states the provision of work under NREGS is far too unpredictable to completely offset the effects of a shock. Under such circumstances, the NREGS would not affect households' risk expectations. Andhra Pradesh, however, is one of the states with the highest number of days of employment generated per rural household. I find that the provision of work in Andhra Pradesh does effectively respond to changes in household demand and thus supports households in managing agricultural production risks.

The estimation strategy employed here builds on the sequenced introduction of the NREGS. Using the introduction of the NREGS at district level, it explores the fact that the scheme was introduced in four out of the six survey districts in 2006 and in the remaining two districts in 2008 and 2009. Because this approach relies heavily on the parallel trends assumption, I perform a number of robustness checks. The use of alternative treatment variables (e.g. block-level spending and employment days generated under the NREGS, as well as households' registration with NREGS) does not change the results. The results are also robust to a range of alternative specifications, to the inclusion of weather data and to changes in household income and wealth.

I find that the key innovation of the Indian public works programme (i.e. giving households the right to work) encourages agricultural households to increase the share of risky but profitable crops, in particular cotton, in their portfolios. The results of this paper suggest that employment guarantees can trigger important gains in agricultural

[1] The block officer is the NREGS official at the block level. The block (in Andhra Pradesh: mandal) is the administrative unit below the district.

productivity in the medium term. These gains go far beyond the direct income effect that the provision of employment in agricultural lean seasons has on the wellbeing of rural households. That increases in productivity and, in turn, in households' incomes can be triggered solely through the insurance effect of an employment guarantee is a very important lesson for other countries with planned or ongoing public works programmes.

The remainder of this paper proceeds as follows: Section 2 introduces a theoretical framework for analysing the effects of an employment guarantee on crop choice. Sections 3 presents the data and summary statistics. Section 4 outlines the estimation strategy. Section 5 presents the empirical results, while section 6 concludes.

2 Risk management and households' crop choices: A theoretical framework

Providing additional employment opportunities to a total of 55 million households has brought about considerable changes in the social and economic realities in India.

The NREGS affects households in rural areas through various channels. The most obvious and so far most intensely researched effect is the increase in available income of those households participating in the programme. This effect is most pronounced for households with surplus labour - namely households where labour supply exceeds labour demand and where regular labour markets fail to absorb this excess. The increase in income resulting from NREGS participation has been shown to raise consumption levels (Jha et al., 2012), increase expenditure on education (Afridi et al., 2012) and to enhance women's empowerment (Pankaj and Tankha, 2010).[2]

Another effect, which is much less well understood, is the insurance effect. It is particularly relevant for households that are highly exposed to covariate shocks such as droughts, floods or large-scale crop diseases. In rural areas of India wages were shown to fall with covariate shocks (Jayachandran, 2006). Such wage fluctuations severely limit households' opportunities to cope with shocks through the labour market. By giving households the right to work and making employment opportunities available independently of shocks, the NREGS greatly influences households' ability to smooth income in the case of a shock. If the insurance effect holds, households could change their production decisions, take more risks and reach higher expected incomes. If a shock then occurs, households can cope with the shock by working for the scheme. Without the shock, it is unlikely that all of these households would participate in the NREGS, because their shadow wages exceed the wage rate paid in the scheme.

Finally, the NREGS is expected to affect wage levels through general equilibrium effects in the village economy. The NREGS was shown to trigger increases in wage levels because wages under the NREGS are in many cases higher than the wages paid for casual work (Azam, 2012; Imbert and Papp, 2013; Berg et al., 2012; Basu, 2013). Increases

[2]Increases in disposable income might also positively influence investment behaviour and the capacity to take risks. Although these effects have not been analysed yet, they are not the main focus of this paper.

in wages could also affect production levels in agriculture because they raise production costs, particularly for large-scale farmers.

In the rest of this paper, I focus specifically on the insurance effect. I develop a theoretical model of household decision-making under uncertainty that shows how the introduction of NREGS can affect crop choice via the insurance effect; the model primarily builds on Dercon and Christiaensen (2011). Taking into account the ideas outlined by Fafchamps (1993) and Van Den Berg (2002), I particularly explore how the sequencing of input allocation, shock realization and harvesting influence production decisions. The possibility to smooth consumption over time is therein constrained by two main factors: the lack of adequate risk management strategies and limited access to credit. Crop choice is first modelled in a world without risk but with imperfect credit markets and then extended to a world with uncertainty. This allows for the isolation of the effects of uncertainty and risk aversion on production decisions. Finally, I will show how the introduction of the NREGS can affect input allocation decisions in both scenarios.

2.1 General setup

I assume that a household engaging in agricultural production, has the choice between two agricultural products Q^d and Q^s. Given that both products are well known to the farmer and have been produced in the region for some time, I can abstract from learning and other sunk costs. These products are produced with two different types of production functions: one is deterministic and the other stochastic.[3] It is also assumed that the risky crop is more productive on average. Both products can be sold at local markets at the same price p.

$$
\begin{aligned}
&Q^d = f^d(a^d, l_1^d, i^d) \\
&Q^s = \epsilon f^s(a^s, l_1^s, i^s) \qquad E[\epsilon] = 1 \\
&\alpha(Q^d + Q^s) = l_2
\end{aligned}
$$

Agricultural production takes place over two periods, the planting and the harvesting seasons. Input allocation at the planting stage defines total yield, which has to be harvested in the second stage. This assumption is in line with earlier work on the sequencing of agricultural production by Fafchamps (1993).

The total yield of both products depends on land a, labour l_1 and input i allocation in period one.[4] Inputs i are defined as a bundle of variable inputs such as seeds, fertilizer and pesticides. I assume that the first period production function is a Cobb-Douglas

[3]The assumption, that one production function is deterministic and the other stochastic is rather extreme. Instead, one would expect both production functions to depend on the realization of random shocks, although to a different extent. However, this simplification is without major impact on the results obtained here.

[4]So far, I have abstracted from fixed capital because the marginal effect of productive capital was found to be relatively low.

type of production function. The total yield of the risky product additionally depends on the realization of a multiplicative, random, serially uncorrelated shock ϵ at the end of the first period. The expected value of this shock is 1; thus in expectation, the production function of the risky crop is just $f^s(a^s, l_1^s, i^s)$. The labour required for harvesting in the second period l_2 is a linear function of realized yields $(Q^d + Q^s)$, where α is a parameter indicating how much labour is needed for harvesting given any realized yield.[5]

I assume that the household maximizes utility from consumption C in both the planting and the harvesting periods. The utility function is additive over both periods and future utility is discounted by the factor δ. The utility function satisfies the usual properties: it is twice differentiable and increases in C but at decreasing rates, $\partial U/\partial C > 0$ and $\partial^2 U/\partial C^2 < 0$. This also implies that the household is risk averse. I abstract from leisure in this model because it will not change the choice under uncertainty.[6] The household generates income from wage employment on local labour markets and from agricultural production. Building on the full-income approach, the household maximization problem can be described as follows:

$$
\begin{aligned}
max \qquad V =& U_1(C_1) + \delta E U_2(C_2) \\
& s.t. \\
& \quad C_1 \leq w_1(T_1 - l_1^d - l_1^s) - g(i^d + i^s) + B \\
& \quad C_2 \leq (p - \alpha w_2^r)(Q^d + Q^s) + w_2 T_2 - (1+r)B \\
& \quad B \leq B^m \\
& \quad a^d + a^s \leq 1
\end{aligned}
$$

Total time endowment is represented by T_1 and T_2. In both periods total time can be allocated between working in the labour market and working in own fields. In the first period, the household obtains income from wage work at level w_1 and from borrowing B. Inputs for agricultural production can be purchased at price g. In the second period, the household obtains income from its own agricultural production $Q = Q^d + Q^s$ and wage work at level w_2. Note here that the household will have to allocate labour to harvesting in order to generate income from agricultural production. Because it seems plausible that the household will always prioritize its own harvest over wage employment, I assume that the household deems the cost of harvesting to equate to reservation wages rather than market wages. It is therefore useful to replace $w_2 l_2$ in the budget constraint with $\alpha w_2^r(Q^d + Q^s)$, where w_2^r is the reservation wage.

Incurred debts will have to be repaid in the second period at an interest rate of r. Input credits are relatively common in rural Andhra Pradesh, although it seems that

[5] Because labour allocation is linear in realized yields, it will be profitable to harvest either the entire crop or nothing at all (depending on wage levels and output prices), thus only allowing for corner solution outcomes.

[6] By dropping leisure, I ignore possible income effects of increases in wage levels on a household's time allocation between labour and leisure. But since my main interest lies in crop choice rather than in production levels, ignoring leisure is not of major concern. Similar approaches can be found in Rosenzweig and Binswanger (1993), Fafchamps and Pender (1997) and Dercon and Christiansen (2011).

the amount of credit conceded is limited by a household's wealth. In the sample around 18% of the households that applied for credit reported not receiving the total amount of credit they applied for. Therefore, B^m describes the maximum amount a household can borrow for productive purposes. In contrast to input credit, consumption credit is much more difficult to obtain and highly expensive as households have to rely mainly on local moneylenders as a source of consumption credit. Because households opt for that source of credit only under extreme circumstances, this model does not allow for any borrowing beyond the harvesting period.

In this setting local labour markets are assumed to function with the option to hire labour in as well as out. In fact, most households in the sample report a range of income sources - of which casual labour features prominently. However, harvest stage wages are assumed to be stochastic and to covary with covariant shocks, such as rainfall shortages. This was shown in the case of rural India by Jayachandran (2006). For most farmers, this means that they can only form expectations about harvest stage wages and face a double risk from rainfall fluctuations: First, their own harvest is likely to fail if there is a rain shortage. Second, they will not be able to find work at adequate wage levels in local labour markets.

Finally, $a^d + a^s = 1$ describes the restrictions on allocable land. I assume that there are no functioning land markets and that owned land is used for own agricultural production or left fallow. This is obviously a simplifying assumption that will not hold everywhere in India. Nonetheless, observed levels of land renting are relatively low in rural Andhra Pradesh and land sales are virtually absent.[7]

The model described so far deviates from standard neoclassical models in that credit and land markets are assumed to be dysfunctional. Given these constraints, the separability of households' production and consumption decisions will not hold even in the absence of risk.

2.2 Deterministic case

First, consider a scenario without uncertainty. In such a world each household maximizes utility by maximizing profits from agricultural production plus income from wage employment. Identical results would be obtained if the household were risk neutral. Because both production functions are deterministic in this scenario, optimal land, input and labour allocation are achieved when their marginal products equal respective prices.

[7] Part of this is due to a very restrictive legal environment that discourages land owners from renting out their land even if it is otherwise left fallow. Also, land prices are very high, which combined with low levels of credit availability makes land acquisition impossible for the majority of households. Those who could afford this rather seek to diversify out of agriculture and move to urban areas.

In the deterministic case, the Lagrange can be written as follows:

$$\begin{aligned}\mathcal{L} =& U_1(C_1) + \delta U_2(C_2) \\ & + \lambda(w_1(T_1 - l_1^d - l_1^s) - g(i^d + i^s) + B - C_1) \\ & + \mu[(p - \alpha w_2^r)(Q^d + Q^s) + w_2 T_2 - (1+r)B - C_2] \\ & + \varphi(B^m - B) \\ & + \rho(1 - a^d - a^s)\end{aligned}$$

Solving the household maximization problem leads to the following decision rules for the allocation of variable inputs to each of the crops:[8]

$$\frac{\partial f^d}{\partial i^d} = \frac{g}{(p - \alpha w_2^r)} \frac{\frac{\partial U_1}{\partial C_1}}{\delta \frac{\partial U_2}{\partial C_2}} \tag{1}$$

$$\frac{\partial f^s}{\partial i^s} = \frac{g}{(p - \alpha w_2^r)} \frac{\frac{\partial U_1}{\partial C_1}}{\delta \frac{\partial U_2}{\partial C_2}} \tag{2}$$

Equations (1) and (2) show the optimal allocation of variable inputs to each of the crops in the first stage. Since decision rules are equal for both crops, optimal allocation will imply that the marginal product of inputs in d is equal to the marginal product of inputs in s. Because realized yield is harvested in the second period, input allocation does not only depend on current prices but also on reservation wages and the discounted marginal utility of consumption in both periods.

$$\frac{\partial U_1}{\partial C_1} = \delta(1+r)\frac{\partial U_2}{\partial C_2} + \varphi \tag{3}$$

Finally, equation (3) describes the optimal consumption rule over both periods given credit constraints: if the credit constraint is binding, φ is greater than zero and the marginal utility from consumption in the planting period will be greater than the marginal utility from consumption in the harvesting period (after accounting for the time discount factor δ and the interest rate r). This means that consumption in the planting stage will be lower than what could be achieved if the credit constraints were not binding.

Including equation (3) into equation (1) also reveals the effect of the credit constraint on input allocation:

$$\frac{\partial f^d}{\partial i^d} = \frac{g(1+r)}{(p - \alpha w_2^r)} + \frac{g\varphi}{(p - \alpha w_2^r)\delta \frac{\partial U_2}{\partial C_2}} \tag{4}$$

If the credit constraint is not binding, $\varphi = 0$, the marginal product of input allocation will be lower and input allocation higher. The same effect holds for input allocation to the stochastic crop Q^s, as well as for labour allocation to each of the crops.

[8] The main focus of this paper is input allocation, but similar results can be obtained for the allocation of labour and land to each of the crops. A detailed derivation of all decision rules can be found in the Mathematical Appendix.

2.3 Introducing uncertainty

When introducing uncertainty, the Lagrange is written as follows:

$$\begin{aligned}\mathcal{L} =& U_1(C_1) + \lambda(w_1(T_1 - l_1^d - l_1^s) - g(i^d + i^s) + B - C_1)) \\ &+ E[\delta U_2(C_2) + \mu[(p - \alpha w_2^r)(Q^d + Q^s) + w_2 T_2 - (1+r)B - C_2]] \\ &+ \varphi(B^m - B) \\ &+ \rho(1 - a^d - a^s)\end{aligned}$$

The household faces uncertainty with respect to the realized yield of the risky crop Q^s and the wage levels in the harvest period w_2. This affects the expectations a household forms about the level of consumption that can be achieved in the second period. When differentiating the Lagrange with respect to the choice variables, the optimal consumption rule is:

$$\frac{\partial U_1}{\partial C_1} = (1+r)\delta\frac{\partial EU_2}{\partial C_2} + \varphi \tag{5}$$

The consumption rule - equation (5) - changes slightly when introducing uncertainty because for any expected consumption level C_2, expected utility $EU_2(C_2)$ will be lower than utility of the expected value $U_2(E(C_2))$, and marginal expected utility will be higher than marginal utility. Since all other variables remain constant, C_2 has to be higher relative to C_1 under uncertainty for the identity to hold. This is equivalent with the well-known argument that risk decreases current consumption levels and enhances savings.

The decision rules for input allocation under uncertainty are the following:

$$\frac{\partial f^d}{\partial i^d} = \frac{g}{(p - \alpha w_2^r)}\frac{\frac{\partial U_1}{\partial C_1}}{\delta\frac{\partial EU_2}{\partial C_2}} \tag{6}$$

$$\frac{\partial f^s}{\partial i^s} = \frac{g}{(p - \alpha w_2^r)}\frac{\frac{\partial U_1}{\partial C_1}}{\delta\frac{\partial EU_2}{\partial C_2}} - \frac{cov(\frac{\partial U_2}{\partial C_2}, \epsilon)}{(p - \alpha w_2^r)\delta\frac{\partial EU_2}{\partial C_2}} \tag{7}$$

Equation (6) shows the allocation rule for inputs to the safe crop. It looks similar to equation (1), except that now the household maximizes expected utility of consumption in the harvest period. Again, marginal expected utility is higher than marginal utility. Thus, under uncertainty, the right-hand side term will be lower than in the deterministic case, implying that the household allocates more inputs to the safe crop than it would in the absence of risk. This reflects the greater weight households put on future consumption than on current consumption as described above.

Equation (7) shows the effect of uncertainty on input allocation to the risky crop. Here the allocation rule changes considerably and the overall effect is less clear. Again, marginal expected utility is higher than marginal utility, thus implying higher input allocation to the risky crop also. However, the covariance between marginal utility of consumption and the random shock ϵ is strictly negative.[9] This term increases the value of the right-hand side of equation (7), which means that input allocation to the risky crop will be lower under uncertainty. Which of the two effects is stronger depends on the degree of risk aversion of the household, expected consumption levels C_2 and the amount of covariance between marginal utility and the random shock. Since the covariance will be stronger with lower wages in period two and with a higher interest rate r, the net effect of uncertainty on input allocation can be expected to be negative in this context.

Irrespective of total levels of input allocation, it can be clearly seen that under uncertainty, input allocation will shift towards the safe crop i^d relative to the risky crop i^s. Thus under uncertainty, the share of risky crops in a household's portfolio will always be lower than in the deterministic scenario.

Again, equations (6) and (7) can be reformulated to include the credit constraint. Then, input allocation to the risky crop is as follows:

$$\frac{\partial f^s}{\partial i^s} = \frac{g(1+r)}{(p-\alpha w_2^r)} + \frac{g\varphi}{(p-\alpha w_2^r)\delta\frac{\partial EU_2}{\partial C_2}} - \frac{cov(\frac{\partial U_2}{\partial C_2},\epsilon)}{(p-\alpha w_2^r)\delta\frac{\partial EU_2}{\partial C_2}} \tag{8}$$

We can see from equation (8) that both risk and credit constraints go in the same direction and reduce the input allocation to the risky crop. More importantly, it also shows that uncertainty reduces input allocation to the risky crop relative to the deterministic crop even if credit constraints are not binding.

2.4 The insurance effect of the National Rural Employment Guarantee Scheme

The insurance effect of the National Rural Employment Guarantee Scheme (NREGS) on households' allocation rules are best represented by an increase in expected harvest stage wages.[10] For households with a labour surplus, other farms offer the best possibility of finding employment during harvest periods; in the case of major weather shocks, they have to expect to not find any employment at all (Jayachandran, 2006). Because the NREGS provides reliable income opportunities throughout the year, households can expect to find employment in the harvest period even in bad years. In other words, the NREGS reduces the covariance between harvest stage wage levels and covariant shocks. The comparative statics in this section show that the introduction of NREGS affects optimal input allocation under certainty differently than under uncertainty.

In the deterministic case, the optimal allocation of input to both crops is as follows:

$$\frac{\partial f}{\partial i} = \frac{g}{(p-\alpha w_2^r)}\frac{\frac{\partial U_1}{\partial C_1}}{\delta\frac{\partial U_2}{\partial C_2}} \tag{9}$$

[9] In a bad state of the world ($\epsilon = 0$) consumption in the second period will be lower and marginal utility higher than in a good state of the world.

[10] Of course, in a scenario without uncertainty, expected wage levels need to be replaced by average wage levels.

An increase in average harvest period wages w_2 affects optimal input allocation by increasing consumption levels that can be realized in the second period. Households that hire labour out (i.e. those whose land is too small to produce at higher levels) will increase consumption. One will thus see a decrease in input allocation for net lenders of labour because of increases in C_2, which will reduce $\partial U_2/\partial C_2$ and increase the second part of the right-hand side of equation (9). The effect of increased wages on agricultural production levels (through consumption) can be understood as a substitution effect. Because working outside the farm becomes more profitable for households with little cultivated land, the allocation of inputs to those lands should decrease from very high levels to more efficient ones.

An entirely different effect can be observed if uncertainty reduces input allocation to risky crops as given by equation (10):

$$\frac{\partial f^s}{\partial i^s} = \frac{g}{(p - \alpha w_2^r)} \frac{\frac{\partial U_1}{\partial C_1}}{\delta \frac{\partial EU_2}{\partial C_2}} - \frac{cov(\frac{\partial U_2}{\partial C_2}, \epsilon)}{(p - \alpha w_2^r)\delta \frac{\partial EU_2}{\partial C_2}} \tag{10}$$

If harvest stage wages increase, we will observe the same effects on marginal utility of consumption as in the deterministic case. Under uncertainty, however, the negative covariance term reduces input allocation to the risky crop, and this effect is now partially offset by an increase in expected harvest stage wages. If possibilities to generate market income improve, shocks will have less effect on consumption in the harvesting period. Because the household knows that it can improve income in instances of negative production shocks by spending more time working for the NREGS, the possibilities to smooth income increase significantly. The more the covariance term on the right-hand side of our equation approaches zero, the more the ratio of inputs allocated to the risky crop (versus the safe crop) will approach the deterministic scenario. This means that even if total input (or similarly labour) allocation is reduced due to the employment guarantee, the share of total inputs allocated to each of the crops will approach the ratio in the deterministic scenario. Interestingly, this effect holds independently of whether credit constraints reduce total input allocation or not.

3 Data

The model specified above is tested using the Young Lives Survey (YLS) data for Andhra Pradesh. The data set covers 3019 households living in six different districts. Three rounds of interviews have been conducted so far (2002, 2007 and 2009/10). Panel attrition is relatively low: 2,910 households were revisited in 2009/10, giving an attrition rate of 3.6% (Galab et al. 2011). For reasons of comparability, only the second (2007) and third (2009/10) rounds are considered in the current analysis. Furthermore, the analysis is restricted to households with non-zero agricultural production in 2007 and 2009/10, which reduces the sample to 1,118 households (2,236 observations).

The selection process of districts for the YLS ensured that all three geographical regions were represented in the survey, as too were the poor and non-poor districts of each region. The districts were classified through economic, human development and infrastructure indicators (Galab et al., 2011). This sample design ensures that the YLS is broadly representative of the population of Andhra Pradesh.

Out of the six survey districts, four introduced the NREGS in phase one (2006) (the treatment group) and the other two districts in phase two (2007) and three (2008) (the control group). The data is clustered on 87 villages in 17 blocks.

Table 1: General household characteristics

	Treatment				Control			
	2007		2009		2007		2009	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Male household head	0.96	(0.20)	0.96	(0.21)	0.97	(0.17)	0.96	(0.20)
Age of household head	41.92	(12.11)	41.54	(10.40)	40.76	(11.63)	41.32	(9.73)
Household size	6.10	(2.62)	5.99	(2.75)	5.57	(2.01)	5.47	(1.99)
Hh head completed primary education	0.33	(0.47)	0.33	(0.47)	0.25	(0.43)	0.25	(0.43)
Wealth index	0.39	(0.14)	0.46	(0.13)	0.39	(0.21)	0.45	(0.19)
Housing quality index	0.48	(0.24)	0.53	(0.23)	0.51	(0.36)	0.57	(0.34)
Consumer durables index	0.18	(0.17)	0.29	(0.17)	0.19	(0.18)	0.26	(0.18)
Housing services index	0.51	(0.14)	0.55	(0.13)	0.46	(0.21)	0.53	(0.18)
Hh benefits from credit/training programme	0.62	(0.49)	0.79	(0.41)	0.57	(0.50)	0.76	(0.43)
Annual income, off-farm activities	25.25	(25.73)	33.06	(37.36)	19.90	(26.24)	24.34	(27.48)
Value of agr. production	28.57	(46.05)	34.27	(55.91)	23.72	(123.03)	25.02	(97.11)
Household registered with NREGS	0.66	(0.47)	0.76	(0.43)	0.00	(0.00)	0.78	(0.41)
Household generated income from NREGS	0.54	(0.50)	0.70	(0.46)	0.00	(0.00)	0.76	(0.43)
Income, NREGS	1.21	(2.36)	2.70	(3.66)	0.00	(0.00)	2.95	(3.57)
Any serious debts	0.63	(0.48)	0.40	(0.49)	0.47	(0.50)	0.27	(0.45)
Able to raise 1000 Rupees in one week	0.61	(0.49)	0.51	(0.50)	0.33	(0.47)	0.59	(0.49)
Observations	769		769		349		349	

Notes: Nominal values in INR 1,000 (constant July 2006).

Summary statistics of general household characteristics are reported in Table 1. In both groups the vast majority of sampled households are headed by males. Table 1 also shows that the average household consists of six members, whose head is around 41 years old. Schooling levels are generally low, with only 33% of household heads having completed primary education in the treatment group compared to 25% in the control group. Household wealth levels have increased over time and are relatively similar across both groups.[11] A high share of households report having access to other government programmes that could affect households' incomes, such as microcredit and training programmes. The percentage of households with access to such programmes in 2007 is slightly higher in the treatment group (62%) than in the control group (57%). Households in the treatment group are also somewhat more likely to have access to financial services in 2007: both the debt incidence (63%) and the reported ability to

[11] The wealth index is calculated as a simple average of housing quality, consumer durables and services. Housing quality is the simple average of rooms per person and indicator variables for the quality of roof, walls and floor. Consumer durables are the scaled sum of 12 variables indicating the ownership of items such as radios, fridges, televisions, phones or vehicles. Services are calculated as the simple average of dummy variables indicating households' access to drinking water, electricity, toilets and fuels. For more information on the wealth index refer to the Young Lives data justification documents at http://www.younglives.org.uk.

raise INR 1,000 within one week (61%) are higher in the treatment group than in the control group (47% and 33%, respectively). Most households generate income from both own farming and off-farm activities - though the latter generates on average less income than the former. Both farm and non-farm incomes are slightly higher in the treatment group than in the control group. Finally, 66% of households in the treatment group report being registered with the NREGS in 2007, and 54% of households report having earned income with the NREGS in the same year.

Table 2: Farming characteristics

	Treatment				Control			
	2007		2009		2007		2009	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Value of agr. production	28.57	(46.05)	34.27	(55.91)	23.72	(123.03)	25.02	(97.11)
Value of agr. production (log)	8.96	(2.64)	9.35	(2.39)	8.15	(3.01)	8.03	(3.42)
Value of variable inputs	14.50	(21.35)	17.52	(20.33)	14.15	(68.45)	14.18	(90.82)
Variable inputs (log)	8.96	(1.10)	9.28	(1.01)	8.25	(1.32)	8.25	(1.22)
Area cultivated (acres)	4.17	(4.72)	4.26	(4.32)	2.67	(5.39)	2.54	(3.25)
Area cultivated (acres, log)	0.93	(1.13)	1.09	(0.85)	0.26	(1.30)	0.40	(1.05)
Irrigated area (% of total)	0.19	(0.32)	0.18	(0.30)	0.15	(0.31)	0.10	(0.25)
Fertilizer (dummy)	0.98	(0.16)	0.99	(0.09)	0.87	(0.34)	0.83	(0.38)
HYV seeds (dummy)	0.77	(0.42)	0.61	(0.49)	0.64	(0.48)	0.52	(0.50)
Produced any: Cotton	0.16	(0.37)	0.27	(0.44)	0.05	(0.23)	0.03	(0.17)
Produced any: Commercial crops	0.07	(0.25)	0.07	(0.26)	0.25	(0.43)	0.28	(0.45)
Share inputs: Paddy rice	0.31	(0.39)	0.29	(0.37)	0.63	(0.40)	0.68	(0.38)
Share inputs: Grams and Pulses	0.02	(0.08)	0.02	(0.08)	0.07	(0.18)	0.05	(0.14)
Share inputs: Cotton	0.11	(0.27)	0.19	(0.33)	0.03	(0.14)	0.02	(0.12)
Share inputs: Groundnuts	0.27	(0.40)	0.28	(0.40)	0.02	(0.09)	0.02	(0.11)
Share inputs: Maize	0.03	(0.14)	0.06	(0.20)	0.00	(0.00)	0.01	(0.06)
Share inputs: Jowar	0.05	(0.15)	0.02	(0.11)	0.01	(0.09)	0.01	(0.05)
Share inputs: Foodgrains	0.04	(0.14)	0.01	(0.09)	0.02	(0.10)	0.01	(0.06)
Share inputs: Oilseeds	0.11	(0.24)	0.06	(0.19)	0.01	(0.04)	0.01	(0.04)
Share inputs: Commercial crops	0.03	(0.14)	0.02	(0.11)	0.16	(0.33)	0.16	(0.30)
Share inputs: Fruits	0.02	(0.11)	0.01	(0.07)	0.01	(0.08)	0.01	(0.04)
Share inputs: Vegetables	0.03	(0.12)	0.03	(0.12)	0.02	(0.11)	0.01	(0.09)
Share inputs: Other crops	0.01	(0.10)	0.01	(0.06)	0.02	(0.11)	0.03	(0.15)
Observations	769		769		349		349	

Notes: Nominal values in INR 1,000 (constant July 2006). Commercial crops exclude cotton.

Table 2 reports the summary statistics of farming characteristics. It shows that agricultural production levels are higher among treatment group households than among control group households. The average amount spent on variable inputs (such as seeds, fertilizer and pesticides), cultivation areas and irrigation levels are all higher in the treatment group than in the control group. Equally, more households in the treatment group report applying fertilizer (98%) and high yielding variety (HYV) seeds (77%) in 2007; in the control group the corresponding shares are 87% and 64%, respectively. Although information about each household's input quantity was not collected, households were asked to report how much they spent on variable inputs for each crop they cultivated. This information is used to compute the share of inputs a household allocates to each crop. As Table 2 shows, paddy rice is by far the most popular crop in both groups. In 2007 31% of all inputs were allocated to rice in the treatment group and 63% in the control group. Other important crops in the treatment group are groundnuts (27%), oilseeds (11%) and cotton (11%). In the control group, production strategies are somewhat different: the main crops after paddy rice are commercial crops - other than cotton - (16%) and grams and pulses (7%). Production strategies seem to have changed considerably in the treatment group, whereas crop shares have remained almost constant in the control group. Interestingly, the proportion of inputs allocated to cotton in the treatment group increased considerably between 2007 (11%) and 2009 (19%).

Table 3: Shocks (sample mean)

	Treatment				Control			
	2007		2009		2007		2009	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Rainfall (deviation)	0.32	(0.28)	0.03	(0.29)	-0.05	(0.16)	0.03	(0.29)
Rainfall (deviation, lag)	-0.39	(0.10)	0.28	(0.28)	-0.12	(0.10)	0.23	(0.23)
Shock: Theft	0.08	(0.26)	0.08	(0.27)	0.03	(0.17)	0.01	(0.09)
Shock: Increases in input prices	0.12	(0.33)	0.25	(0.43)	0.08	(0.27)	0.13	(0.33)
Shock: Decreases in oputput prices	0.10	(0.30)	0.25	(0.43)	0.03	(0.18)	0.03	(0.17)
Shock: Death of livestock	0.12	(0.33)	0.19	(0.39)	0.09	(0.29)	0.06	(0.24)
Shock: Drought	0.59	(0.49)	0.16	(0.37)	0.16	(0.36)	0.04	(0.19)
Shock: Flooding	0.14	(0.35)	0.04	(0.21)	0.09	(0.28)	0.05	(0.22)
Shock: Erosion	0.00	(0.06)	0.01	(0.12)	0.00	(0.00)	0.00	(0.00)
Shock: Hailstorms	0.01	(0.11)	0.01	(0.08)	0.00	(0.00)	0.01	(0.09)
Shock: Pest or Diseases	0.21	(0.40)	0.20	(0.40)	0.09	(0.29)	0.10	(0.30)
Shock: Crop failures	0.32	(0.47)	0.54	(0.50)	0.33	(0.47)	0.19	(0.39)
Observations	769		769		349		349	

Table 3 reports the occurrence of different shocks in both groups and in both periods. Rainfall deviation and rainfall deviation (lag) describe the deviation of annual cumulative rainfall levels from their long-term average (2002-2011).[12] Lagged rainfall captures the cumulative rainfall in the agricultural year preceding the input allocation decision under consideration. In 2007 lagged rainfall was lower than average for both groups, although the shock seems to have affected the treatment group more severely, which had also more households report having been affected by drought. This picture is reverted in 2009, with both the treatment and control groups experiencing good years in terms of rainfall.

Lastly, Table 4 reports the treatment intensity of the NREGS at block level in both groups and the village-level availability of other government programmes. As expected, block-level cumulative spending under the NREGS is considerably higher in the treatment group than in the control group. Also, the number of person-days generated per job card was much higher in blocks belonging to phase one districts than in the remaining districts in the financial year 2007/08. By the following year, however, phase two and three districts provided almost as many person-days of employment per job

[12] Block-level precipitation data were obtained from the Directorate of Economics and Statistics, Andhra Pradesh

card as phase one districts. In the availability of other government programmes, both groups show substantive differences as well. Watershed development programmes are much more common in treatment villages than in control villages, reflecting lower average rainfall levels in treatment areas. In contrast, more villages in the control group had other public work programmes and crop insurance schemes in place in 2007. The high availability of public works programmes in the control group could be potentially problematic and will be addressed in more detail later on. It is worth mentioning, however, that the key innovation of the NREGS (i.e. providing a legal entitlement to work) and the amount of funds disbursed under the NREGS were unprecedented compared to other public works programmes in India.

4 Estimation strategy

The key prediction of the model described in section 2 is that an increase in expected labour market wages in the harvesting period, *ceteris paribus*, increases the share of inputs allocated to risky crops if households were previously constrained in their crop choice by high levels of uncertainty regarding output levels and dysfunctional insurance markets. It is not possible, however, to test this hypothesis directly for two reasons. First, households' expectations with regard to wages depend on a range of factors that are neither observable to the researcher nor able to be perfectly captured by observed village-level wages (such as perceived access to the labour market). Second, a range of unobserved village characteristics may change over time and those changes will probably influence both expected labour market wages and farmers' crop choice.

To circumvent the problems mentioned above, I explore the availability of the NREGS as a source of exogenous variation in expected labour market wages during the harvest period. As argued in section 2.4, the introduction of NREGS increases expected wages in the harvest period because employment opportunities through the NREGS do not depend on favourable weather outcomes and hence do not covary with village-level shocks. It is important to notice here that the NREGS does not only affect households' crop choices through the insurance effect - which is the main focus of this paper. Because

Table 4: Village level availability of NREGS and other programmes

	Treatment		Control	
	Mean	SD	Mean	SD
Cumulative expend. NREGS (April 2008)	504.9	(211.6)	191.2	(150.6)
Cumulative expend. NREGS (April 2008, log)	6.12	(0.48)	4.51	(1.78)
Cumulative expend. NREGS (April 2009)	889.7	(358.2)	482.4	(290.8)
Cumulative expend. NREGS (April 2009, log)	6.69	(0.48)	5.96	(0.70)
Persondays per job card NREGS (FY 2007/08)	19.7	(7.28)	13.1	(10.2)
Persondays per job card NREGS (FY 2008/09)	19.9	(9.54)	19.6	(8.84)
Availability: Watershed development (2007)	0.43	(0.50)	0.12	(0.33)
Availability: Public works (2007)	0.52	(0.50)	0.80	(0.40)
Availability: Crop insurance (2007)	0.49	(0.50)	0.72	(0.45)

Notes: Nominal values in current INR 100,000.

increases in available income and wealth due to the NREGS might also influence a household's ability to cope with shocks, it is essential to control for these changes in order to isolate the insurance effect. The model to be estimated can be written as follows:

$$i^s_{it}/(i^d_{it} + i^s_{it}) = \beta_0 + \beta_1 D_{it} + \beta_2 X_{it} + \beta_3 Z_{it} + u_i + \upsilon_{it} \tag{11}$$

The dependent variable is the ratio of inputs allocated to risky crops and D_{it} represents a household's access to the NREGS. Let X_{it} be a set of time-varying household characteristics that affect preferences and crop choice in particular (such as education, wealth, income and past experience with shocks) and u_i be time-constant unobserved household characteristics (such as risk aversion, farming ability and land quality). Z_{it} is a set of time-varying village-level characteristics (e.g. weather trends, extension services, prices, etc.) and υ_{it} is an independent and identically distributed (iid) error term.

I use four different treatment variables. First, I explore the universal nature of the NREGS by coding as 'treated' those households based in districts where the NREGS had already been introduced at the time of taking input allocation decisions.[13] Second, I use block-level disbursements under the programme as an indicator of the intensity of treatment, arguing that households living in blocks with higher past disbursements have higher expectations about the availability of employment in situations of need. Third, following the same logic, I use the lagged annual total of employment person-days generated per job card at the block-level. Fourth, I explore the self-selection of households on to the programme in order to increase the robustness of my results. When doing so, I match households according to their probability to register with the NREGS at early stages of programme implementation.

To estimate equation (11), I apply fixed effects regression models. This allows me to control for unobserved time-constant household- and village-level characteristics that might influence the outcome variable.[14] In the fixed effects model β_1 is an unbiased estimate of the true effect if two assumptions are fulfilled: the parallel trends assumption and the assumption that treatment is not correlated with potential outcomes.

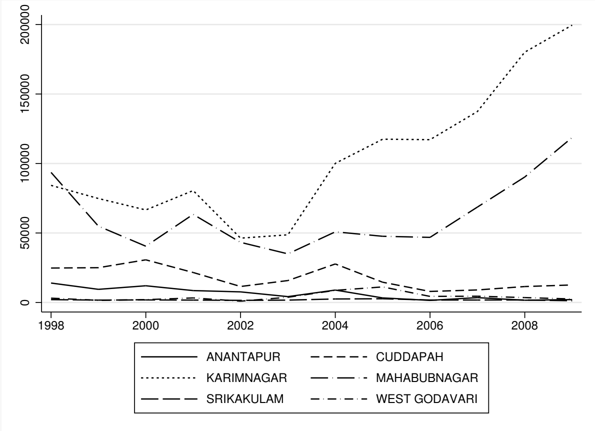
The parallel trends assumption could have been tested if the first round of the YLS data had included information on crop choice, which unfortunately is not the case. Instead, I have to rely on the Land Use Statistics provided by the Ministry of Agriculture. District-wise time trends in areas under cotton cultivation are displayed in Figure 1. It shows that cotton production levels vary across districts, although they moved in more or

[13]Given the size of the programme and the huge awareness campaigns undertaken at the beginning of implementation, it seems valid to assume that households in rural Andhra Pradesh form expectations about income opportunities through the NREGS based on the local availability of the programme and not only based on being registered with the programme.

[14]In the fixed effects model, the coefficient of D_{it} is only identified if D_{it} equals 0 for all households in the baseline and 1 for some households in the follow-up. This might seem arbitrary because the introduction of the NREGS began in April 2006, which was before round two interviews of the YLS were conducted. However, the round two survey questions refer to input allocation decisions taken between June 2005 and February 2006, which was before the implementation of the NREGS started. At this point in time households would not yet have experienced the effects of the NREGS, which is why the treatment variable in this round is coded zero.

less similar trends until 2006. To further correct for different initial levels and potentially different trends across regions, I employ matching techniques (as mentioned above) and perform all analyses also for the subsample of households living in phase one districts.

Figure 1: District-wise land use statistics for cotton



Source: Directorate of Economics and Statistics, Department of Agriculture and Cooperation, Ministry of Agriculture, GoI

It also seems plausible to assume that treatment is not correlated with potential outcomes. First, by using explanatory variables at the district or the block level, I can account for potential biases arising from households' self-selection on to the programme.[15] Second, the introduction of the NREGS at the district level and the treatment intensity at the block level seem to be exogenous to potential outcomes. At the district level, the NREGS should have been introduced in the poorest districts first.[16] This could potentially bias the estimates downwards because poorer districts are less likely to have extension services and marketing structures in place that would enable households to seize the opportunity to plant more profitable cash crops. However, in most states - and in Andhra Pradesh in particular - the prioritization of the poorest districts was not systematically implemented. In this sample the general economic characteristics of treatment and control districts do not differ greatly (Table B.1). The treatment intensity at the block level should also be exogenous to potential outcomes. Estimates could be biased if funds allocated to blocks responded to rainfall shocks and if these rainfall shocks also affected a household's input allocation decision. However, the amount of

[15]In those specifications where I rely on households' registration with the NREGS as a treatment variable, I employ matching techniques to reduce self-selection bias.

[16]The implementation of the NREGS was intended prioritize India's 200 poorest districts, subsequently extending to the remaining districts. India has a total of 655 districts, of which 625 had introduced the NREGS as of 2008. The 30 remaining district were urban districts. In 2003 the Planning Commission of India elaborated clear rules stating which districts should be included in which round of implementation of the NREGS. However, the process of district selection was extremely politically sensitive due to the huge size and financial relevance of this programme, which saw the rules not strictly followed. The result is that we find both wealthier and poorer districts among all three groups.

funds to be sanctioned per block is defined between December and March for the following financial year (April to March).[17] Since I am using lagged values of disbursed funds and employment days, these amounts are fixed 18 months before the decision on input allocation is taken and 6 months before the beginning of the rainy season, which above all influences a household's production decision.[18]

Studies that work with a small number of clusters always face the challenge of adequately adjusting standard errors. Throughout the paper, I calculate Eicker-White standard errors clustered at the village level. However, since the treatment variables are mostly fixed within a district or block, these standard errors are likely to be downward biased (Cameron et al., 2008). Clustering standard errors at higher levels of aggregation (e.g. block or district) may not be consistent either, because the number of clusters would be too small. In cases of very few clusters, Cameron et al. (2008) suggest using a wild cluster-bootstrap, which resamples clusters instead of individual households. This approach was applied, inter alia, by Adrianzen (2014) to data clustered in 26 villages and by Akosa Antwi et al. (2013) to 28 quarter-year groups. As a robustness check, I perform the wild cluster-bootstrap at the sub-district level (17 blocks). The resulting p-values vary according to the treatment variable considered. For the introduction of NREGS at the district level, the corresponding p-value is 3%. For cumulative spending and number of workdays generated, the p-values are 5% and 16%, respectively.[19]

5 Results

This section starts by presenting estimates for an agricultural production function, which identifies profitable crop choices for farmers in this sample. This section also discusses the relevance of risk as a potential constraint to producing these crops. It proceeds by assessing the extent to which the NREGS can actually support households in this sample in coping with shocks, which is the precondition for expecting any insurance effect. This section then analyses the effects of the NREGS on households' crop choices. A number of robustness checks are presented, and the section concludes with some evidence on the heterogeneity of the observed effects.

[17] The amount sanctioned depends on a village's list of projects, which has to be approved by the block programme officer. The block programme officer has to estimate employment demand for the following financial year and consolidate all village lists before submitting the Block Employment Guarantee Plan to the district programme coordinator. The district council (zilla parishad) has to approve all plans before transferring them to the state government.

[18] The rainy season in Andhra Pradesh if from June to September, while planting of cotton starts in May at the earliest and needs to be completed before end of July. The allocation decision is thus primarily influenced by lagged rainfall levels because current levels are not yet fully realised at the time of sowing.

[19] The wild cluster-bootstrap reports rejection rates instead of standard errors, which is why I report clustered standard errors throughout the text. Implementation in Stata is done with the programme cgmwildboot.ado written by Judson Caskey.

5.1 Identifying profitable production strategies

To identify viable strategies for households to improve their income from agricultural production, I estimate a standard Cobb-Douglas production function, linking the total value of agricultural output to input allocation, plot size and crop choice. The equation is estimated in random effects and fixed effects models. As can be seen in Table 5, both models provide similar results.

As Table 5 shows, the most important determinant of agricultural output is the level of inputs allocated.[20] Additionally, the total cultivated area and the share of area under irrigation seem to determine output levels. The dummies indicating whether or not a household applied fertilizer or high yielding variety (HYV) seeds are not statistically significant. This might seem somewhat surprising, but since expenditure on fertilizer and seeds is included in variable inputs, one should not attribute too much weight to this finding. Finally, the results presented in Table 5 suggest that households could significantly raise the value of their agricultural production if they were to increase the share of inputs allocated to cotton or to other commercial crops relative to food crops.[21] Producing fruits could also lead to considerably higher incomes from agricultural production. In contrast, producing a higher share of oilseeds or groundnuts would apparently reduce the total value of agricultural production.

If households are able to increase the value of their agricultural production by producing a greater share of profitable crops, it raises the question why they do not do so. Obviously, it may not be possible to generalize these results to extended periods of time if, for instance, the two survey years were exceptionally dry or exceptionally productive. Therefore, I additionally consider state-level statistics on the returns per hectare for major crops between 1996 and 2009.[22] Figure 2 plots the average returns of different crops against the standard deviation of these returns for the years 1996 to 2006 in Andhra Pradesh. These statistics suggest that cotton has considerably higher average returns than food crops, groundnuts and other oilseeds. Figure 2 also shows a clear positive relationship between average returns and their volatility, indicating that risks associated with the production of these crops could explain why households produce so little of them.

Two factors in particular could be driving the observed volatility in returns: yield fluctuations and price fluctuations. Yields of commercial crops are often more volatile than yields of food crops. For example, the variation coefficient of crop yields for rice is 0.1 in the years between 1990/91 and 2008/09. The corresponding value for cotton is 0.24.[23] At the same time, most of the commercial crops are not eligible for minimum support prices. Figure 3 displays the district-wise development of nominal farm harvest

[20] This is the total amount spent on variable inputs, such as seeds, fertilizer, pesticides and so forth. Manual labour is accounted for if hired in. Household labour was not included in the regression, because this information was not collected in the third round of interviews.

[21] Foodgrains were used as the reference category in the estimation. Commercial crops include coffee, tobacco, sugar cane, flowers, eucalyptus, ginger, garlic, black pepper, chillies, turmeric and other spices.

[22] Unfortunately, these statistics are only available at state level and only for very few crops.

[23] Author's calculation based on district-wise crop production statistics provided by the Indian Ministry of Agriculture.

Table 5: Agricultural Production Function

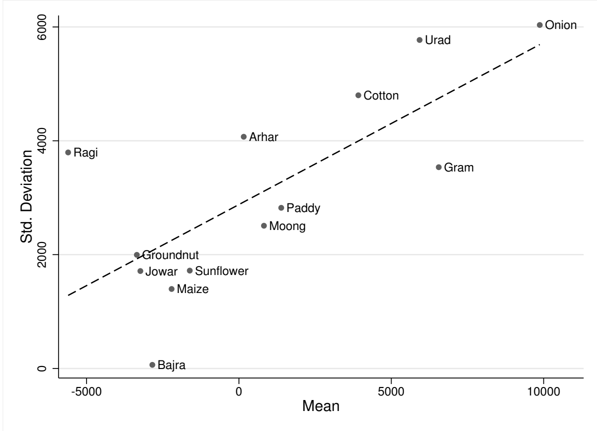
	Random Effects	Fixed Effects
Variable inputs (log)	0.649***	0.553***
	(0.040)	(0.040)
Area cultivated (acres, log)	0.195***	0.094**
	(0.034)	(0.035)
Irrigated area (% of total)	0.156*	0.089
	(0.073)	(0.101)
Fertilizer (dummy)	-0.128	-0.104
	(0.084)	(0.157)
HYV seeds (dummy)	0.050	0.073
	(0.038)	(0.047)
Share inputs: Cotton	0.179*	0.326*
	(0.079)	(0.129)
Share inputs: Groundnuts	-0.409**	-0.286*
	(0.128)	(0.130)
Share inputs: Oilseeds	-0.474***	-0.565**
	(0.106)	(0.188)
Share inputs: Commercial crops (excl. cotton)	0.454***	0.421*
	(0.137)	(0.204)
Share inputs: Fruits	0.439+	0.678**
	(0.233)	(0.252)
Share inputs: Vegetables	0.221	0.252
	(0.203)	(0.312)
Rainfall (deviation)	0.183**	0.181*
	(0.064)	(0.071)
Year 2009 (dummy)	0.102	0.140*
	(0.075)	(0.070)
Observations	2067	2067

Clustered standard errors in parentheses.

Shocks and cluster dummies included, but not reported. Foodgrains is reference category.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

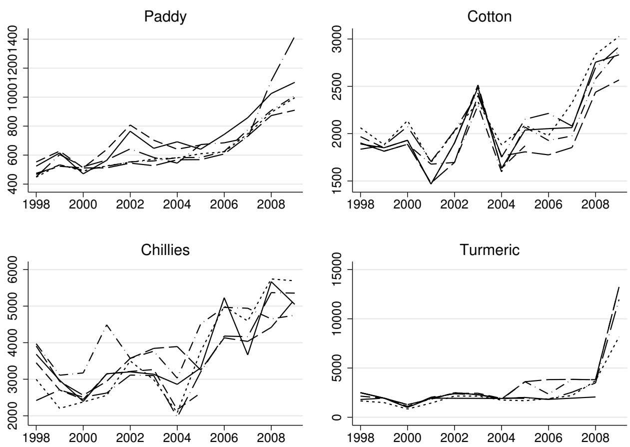
Figure 2: Returns per hectare of selected crops



Source: Directorate of Economics and Statistics, Department of Agriculture and Cooperation, Ministry of Agriculture, GoI

prices of paddy rice and different commercial crops (e.g. cotton, chillies and turmeric) between 1998 and 2008. It can clearly be seen that commercial crop prices varied much more during the reference period than the price of paddy rice.

Figure 3: District-wise farm harvest prices of selected crops (INR per quintal)



Source: Directorate of Economics and Statistics, Department of Agriculture and Cooperation, Ministry of Agriculture, GoI

Of course there could be other explanations as to why households produce so few commercial crops and such little cotton. High upfront costs, for example, could constrain the production of these crops. However, estimated production costs were higher for paddy rice than cotton in the financial year 2005/06. With production costs of INR 29,256 per hectare, rice cultivation was somewhat more expensive than cotton cultivation

(INR 27,625 per hectare).[24] It thus seems reasonable to assume that risk is an important factor in explaining the relatively limited production of cotton and other commercial crops in the sample.

5.2 Does the NREGS support households in coping with shocks?

If risk is a relevant constraint for households' production decisions, the provision of an employment guarantee should enable households to grow a larger share of risky crops. This is the main prediction of the theoretical model presented in this paper. Crucial to this prediction are households' expectations about opportunities to smooth income in the event of a shock. Therefore, we need to understand the extent to which the NREGS helps households in coping with shocks.

To begin with, Andhra Pradesh is particularly suited to studying the question of interest because it is one of the best performing states in India in terms of the number of workdays generated per household and meeting the demand for work (Dutta et al., 2012). Regarding outreach, only Chhattisgarh, West Bengal, Madya Pradesh and Rajastan reached higher proportions of rural households in the financial year 2009/10 (MoRD-GoI, 2012).[25]

I additionally test whether deviations from mean rainfall levels, as well as households' self-reported shocks, drive changes in the number of days households work under the NREGS. I argue that the NREGS will have an insurance effect only if work provision sufficiently reacts to increasing demand in the case of a shock. This question is tested in a fixed effects model. The results are reported in Table 6. In the first column, the total number of days worked in the past 12 months is the dependent variable; in the second column it is the log of this variable. The estimation is also restricted to phase one districts; thus only households who had access to the NREGS in both survey rounds are considered.

The results suggest that the number of days worked for the NREGS changes considerably with variation in rainfall levels. The greatest change is observed for lagged rainfall levels - that is, cumulative rainfall in the agricultural year preceding the period of reference. The coefficient of the lagged rainfall variable is large and negative, which implies that households worked more for the NREGS if lagged rainfall levels were below average and worked less if lagged rainfall was above average. This supports the assumption that the NREGS helps households in coping with shocks, because households use the programme to smooth income ex post - for instance, after harvest and after agri-

[24] Author's calculation based on cost of cultivation statistics, provided by the Directorate of Economics and Statistics, Andhra Pradesh.

[25] At the same time, Andhra Pradesh has been a forerunner in terms of innovative approaches to the implementation of the NREGS. First, it has a lot of experience with performing social audits to increase accountability within the scheme. Second, it was one of the first states to cooperate with IT enterprises to strengthen the efficiency of administrative processes. To increase transparency, entries on muster rolls and the number of workdays generated per job card holder, inter alia, are publicly accessible. Nonetheless, the programme continues to be implemented in a top-down manner in Andhra Pradesh. Usually, work is not generated upon demand, rather work applications are only accepted if there is work available.

Table 6: Number of days worked with NREGS (Fixed Effects)

	NREGS days	NREGS days (log)
Rainfall (deviation, lag)	-51.268*	-2.387***
	(19.317)	(0.537)
Rainfall (deviation)	-23.269**	-0.604
	(8.366)	(0.377)
Area cultivated (acres, log)	3.089+	0.105
	(1.744)	(0.082)
Wealth index	-6.569	0.206
	(19.324)	(0.703)
Hh benefits from credit/training program	12.046**	0.425**
	(3.651)	(0.156)
Self-reported shock	1.592	0.180+
	(3.177)	(0.105)
Year 2009 (dummy)	50.538***	2.247***
	(10.805)	(0.241)
Observations	1528	1528

Clustered standard errors in parentheses.

Cluster dummies and self reported shocks included, but not reported

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

cultural products have been sold. Similar evidence is provided by Johnson (2009), who finds that the number of days households work for NREGS increases if rainfall levels are lower than average.

Table 6 also shows how important maturation of the programme is. A large share of the variance in the number of days worked for the NREGS can be explained by time alone. In contrast, wealth levels do not seem to influence the dependent variable, and the size of the cultivated area is only statistically significant in one model. This is probably due to the limited variation of this variable over time.[26] Interestingly, self-reported shocks do not seem to influence the dependent variable very much. The variable is coded as one of a household reported any of 12 self-reported shocks related to agricultural production. Although the coefficient has the right sign, it is not very high and only weakly statistically significant in one of the specifications. This might be the case for two reasons. First, self-reported shocks refer to any shock in the four years preceding the date of the interview, which might simply be too imprecise to capture the effect of shocks on individual labour allocation. Second, and potentially more problematic, is that because the number of days a household works for the NREGS does not only depend on each household's demand for work but also on the provision of work, it may be that the provision of work reacts to major covariate shocks (e.g. droughts) but does not respond to individual changes in the demand for work following idiosyncratic shocks. It is thus possible that households wanted to work for the scheme to smooth income after idiosyncratic shocks, but the provision of labour did not react to this sufficiently.

[26] A positive coefficient could indicate programme's capture by wealthier households. But a further investigation of this issue is beyond the scope of this paper.

To quantify the contribution of the NREGS to households' risk coping, I compare agricultural losses due to rainfall shortages with income gains through the NREGS. The agricultural production function estimated in section 5.1 suggests that a 25% decrease in annual rainfall would reduce agricultural output by 4.5%. For the average household, this implies a nominal loss of about INR 1,430 (in constant July 2006 values). The same deviation in lagged rainfall would lead households to work about 12.8 days more for the NREGS, which would provide an additional income of INR 820 (at mean wages observed in the sample). The NREGS thus allows households to compensate about 57% of agricultural production losses caused by rainfall shortages. Since rainfall fluctuations are among the most important sources of risk for rural households, these results suggest that the NREGS could indeed have an insurance effect in Andhra Pradesh.

5.3 The effects of the NREGS on households' crop choices

In this section I estimate the effect of the NREGS on households' input allocation to cotton. As described in section 4, equation (11) is tested in a linear fixed effects model. To isolate the insurance effect described in section 2.4, I control for variables that might be affected by the NREGS and might influence a household's crop choice through effects other than the insurance effect. These variables include household off-farm income and wealth, as well as key farming characteristics, such as the size of cultivated land, irrigation and total value of variable inputs allocated.[27]

Table 7 reports the effects of the NREGS on households' share of inputs allocated to cotton. In these specifications I also control for self reported shocks, access to other government programmes and changes in rainfall levels (current and lagged). Additionally, a time dummy is included to control for state-wide changes in input and output prices, weather trends that are not captured by rainfall data and other changes at the state level that could influence a household's crop choice.

The results show a positive and statistically significant effect of the NREGS on households' cotton production. Column 1 suggests that the share of inputs allocated to cotton is 10 percentage points higher if households have access to the NREGS at the district level. Given that the average share of inputs allocated to cotton did not exceed 11% in these districts in 2007, the magnitude of this effect is striking. In columns 2 and 3 I also test for the effects of cumulative expenditure and total employment generated per job card under the NREGS at block level. In these specifications I can also control for region-specific time trends.[28] Both variables seem to have positive and statistically significant effects on a household's allocation of inputs to cotton.

In terms of economic relevance, the results suggest that per additional day of employment generated in the block in the previous financial year, each household would

[27]Household off-farm income consists, inter alia, of income generated through the NREGS in the past 12 months. Optimally, this should be a lagged value because input allocation decisions are taken at the beginning of the season, while the income variable refers to the time period shortly after these allocative decisions were taken. Unfortunately, the survey does not include this information.

[28]In Andhra Pradesh there are three different climatic regions: Coastal Andhra, Telangana and Rayalseema.

Table 7: Effect of the NREGS on inputs allocated to Cotton (Fixed Effects)

	(1)	(2)	(3)
NREGS introduced in district	0.099**		
	(0.033)		
Cumulative expend. NREGS (April 2008, log)		0.041**	
		(0.016)	
Persondays per job card NREGS (FY 2007/08)			0.007***
			(0.002)
Variable inputs (log)	0.069***	0.065***	0.062***
	(0.018)	(0.017)	(0.017)
Area cultivated (acres, log)	-0.006	-0.004	-0.006
	(0.008)	(0.008)	(0.008)
Irrigated area (% of total)	-0.037	-0.053**	-0.069**
	(0.022)	(0.020)	(0.020)
Annual income, off-farm activities (log)	-0.006	-0.007	-0.009*
	(0.005)	(0.004)	(0.004)
Wealth index	-0.023	-0.071	-0.067
	(0.074)	(0.075)	(0.072)
Hh benefits from credit/training program	-0.009	0.001	0.003
	(0.014)	(0.014)	(0.015)
Rainfall (deviation, lag)	-0.104	-0.123	-0.159*
	(0.059)	(0.065)	(0.070)
Year 2009 (dummy)	0.031	-0.148	-0.038
	(0.031)	(0.075)	(0.032)
Observations	2236	2236	2236

Clustered standard errors in parentheses

Dummy for self reported shocks & region-year dummies (col. 2 & 3) included, but not reported.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

increase the share of inputs allocated to cotton by 0.7 percentage points. One standard deviation increase in the number of person-days generated per job card (7.3) would increase a household's input allocation to cotton by 5.1 percentage points and raise net income from agricultural production, *ceteris paribus*, by about INR 486 (in constant July 2006 values). This is particularly interesting from a cost-benefit perspective, since these net income gains are slightly higher than the wage cost (evaluated at the sample average) of creating that many days of employment under the NREGS, e.g. INR 467. Of course, wage costs make up for only a part of overall programme costs and not all of the NREGS participants own their own land, but nevertheless the magnitude of this effect is striking.

5.4 Robustness checks

Because the results presented so far rely heavily on the parallel trends assumption, I perform a number of robustness checks. As a first robustness check, I test whether households that registered with the NREGS change their input allocation more strongly than households who are not registered with the NREGS. To account for potential self-selection bias, I match households on their probability to register with the NREGS by using entropy balancing, a method developed by Hainmueller (2012). Entropy balancing seems to outperform most existing matching algorithms in terms of the balance reached on the entire set of relevant covariates (Hainmueller, 2012). The matching algorithm assigns weights to all observations in the control group such that the distribution of selected variables matches the observed distribution in the treatment group. These weights can then be used as sampling weights in the estimation.[29] I match households on the mean, variance and skewness of variables that determine a household's registration with the NREGS and potentially influence post-treatment outcomes, such as cost incurred in agricultural production, total cultivated area, percentage of area irrigated, fertilizer application, wealth levels and off-farm income and household characteristics (e.g. education, age and sex of the household head; indebtedness; and the ability to raise INR 1,000 in one week). The resulting covariate balance is displayed in Table 8. As we can see, entropy balancing ensures a perfect balance on all variables included.

Table 9 reports the effects of registering with the NREGS on input allocation to cotton. I find that households that already registered with the NREGS in 2007 are more likely to grow risky crops such as cotton. Four different specifications are presented: Column 1 shows the estimation results in the full sample without matching. Column 2 shows the same estimation excluding all households that did not register with the NREGS by 2009.[30] Column 3 shows the estimation results for the matched sample. As we can see, the effects are only slightly smaller when matching households on their probability to register with the NREGS. This suggests that most of the factors that

[29]Since I estimate the model on a balanced sample, the same weights can be applied to the 2009/10 round of interviews.

[30]This is to exclude all households from the sample that - either because they consider it socially undesirable or because they have other means of risk coping - would probably never register with the NREGS.

Table 8: Weighted summary statistics (2007)

	Treatment		Control			
			(not matched)		(matched)	
	Mean	SD	Mean	SD	Mean	SD
Value of agr. production (log)	8.89	(2.53)	8.56	(2.97)	8.95	(2.56)
Variable inputs (log)	8.89	(1.04)	8.61	(1.34)	8.89	(1.06)
Area cultivated (acres, log)	0.86	(1.17)	0.61	(1.26)	0.86	(1.11)
Irrigated area (% of total)	0.15	(0.30)	0.20	(0.33)	0.15	(0.29)
Fertilizer (dummy)	0.97	(0.16)	0.92	(0.27)	0.97	(0.16)
Annual income, off-farm activities (log)	9.75	(0.86)	9.41	(1.66)	9.75	(0.88)
Housing quality index	0.46	(0.23)	0.51	(0.32)	0.46	(0.26)
Consumer durables index	0.15	(0.14)	0.21	(0.19)	0.15	(0.14)
Housing services index	0.50	(0.13)	0.49	(0.20)	0.50	(0.15)
Male household head	0.96	(0.19)	0.96	(0.20)	0.96	(0.19)
Age of hh head	41.27	(12.09)	41.80	(11.86)	41.27	(11.52)
Household head is literate	0.32	(0.47)	0.29	(0.45)	0.32	(0.47)
Any serious debts	0.67	(0.47)	0.51	(0.50)	0.67	(0.47)
Able to raise 1000 rupees in one week	0.57	(0.50)	0.49	(0.50)	0.57	(0.50)
Observations	506		612		601	

possibly biasing our estimates were already accounted for by applying fixed effects models. Overall, the effects are of a similar size in most specifications and very close to the estimates presented in Table 7, column 1. Column 4 shows the estimation results for the full sample without matching. Here, being registered by 2009 is the main explanatory variable. As we would expect, households that registered with the NREGS only by 2009, did not alter their input allocation in a meaningful way.

As a second robustness check, I perform all estimations presented so far for the subsample of households living in treatment areas (in phase one districts only); the results are reported in Table 10. In this specification, coefficients are somewhat smaller but still positive and statistically significant at the 10% level. Again, three different specifications are presented. Column 1 presents results for the full sample in phase one districts without matching. Column 2 presents the estimation results for all households excluding those who did not register with the NREGS by 2009. Column 3 presents results for the matched sample. Again, matching households on their probability to register with the NREGS does not greatly change the results. Table B.2 in the Appendix reports the results of the intensity of the treatment in phase one districts. Once more, coefficients continue to be statistically significant. For expenditure under the NREGS, the coefficient becomes even larger when the sample is reduced to phase one districts only.

Of course, one might be concerned that the observed effects are driven by factors other than the insurance effect of the NREGS. I cannot fully exclude the possible influence of unobserved time-varying factors on these results. Nonetheless, I attempt to account for as many potential confounders as possible. In addition to the robustness checks presented so far, I also test the extent to which treatment effects vary depending on the initial presence of other government programmes, such as watershed development

Table 9: Effect of the NREGS on inputs allocated to Cotton by registration status (Fixed Effects)

	(1)	(2)	(3)	(4)
NREGS registered (2007)	0.074*	0.085*	0.064*	
	(0.030)	(0.036)	(0.027)	
NREGS registered (2009)				0.015
				(0.017)
Variable inputs (log)	0.073***	0.080***	0.090***	0.077***
	(0.018)	(0.018)	(0.021)	(0.019)
Area cultivated (acres, log)	-0.007	-0.003	-0.016	-0.008
	(0.008)	(0.009)	(0.011)	(0.008)
Irrigated area (% of total)	-0.039+	-0.041	-0.048+	-0.035
	(0.021)	(0.027)	(0.025)	(0.021)
Annual income, off-farm activities (log)	-0.005	-0.004	-0.007	-0.006
	(0.005)	(0.005)	(0.007)	(0.005)
Wealth index	-0.015	0.045	-0.042	-0.008
	(0.074)	(0.091)	(0.076)	(0.075)
Hh benefits from credit/training program	-0.009	-0.001	-0.006	-0.008
	(0.014)	(0.018)	(0.017)	(0.014)
Rainfall (deviation, lag)	-0.074	-0.077	-0.094	-0.030
	(0.055)	(0.059)	(0.059)	(0.049)
Year 2009 (dummy)	0.048	0.036	0.069+	0.044
	(0.032)	(0.035)	(0.037)	(0.031)
Observations	2236	1712	2214	2236

Clustered standard errors in parentheses.

Dummy for self reported shocks included, but not reported.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Inputs allocated to Cotton in Phase I districts (Fixed Effects)

	(1)	(2)	(3)
NREGS registered (2007)	0.046^{+}	0.048	0.061*
	(0.025)	(0.034)	(0.028)
Variable inputs (log)	0.095***	0.103***	0.094***
	(0.025)	(0.025)	(0.025)
Area cultivated (acres, log)	-0.016	-0.012	-0.021
	(0.011)	(0.012)	(0.014)
Irrigated area (% of total)	-0.051^{+}	-0.043	-0.027
	(0.026)	(0.029)	(0.025)
Annual income, off-farm activities (log)	-0.008	-0.011	-0.011
	(0.007)	(0.007)	(0.010)
Wealth index	-0.018	0.029	-0.088
	(0.089)	(0.123)	(0.093)
Hh benefits from credit/training program	-0.002	0.007	-0.017
	(0.018)	(0.023)	(0.028)
Rainfall (deviation, lag)	-0.193*	-0.206*	-0.143*
	(0.084)	(0.085)	(0.071)
Year 2009 (dummy)	0.152*	0.156*	0.110*
	(0.058)	(0.063)	(0.050)
Observations	1538	1166	1530

Clustered standard errors in parentheses.

Dummy for self reported shocks included, but not reported. Phase I districts only.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

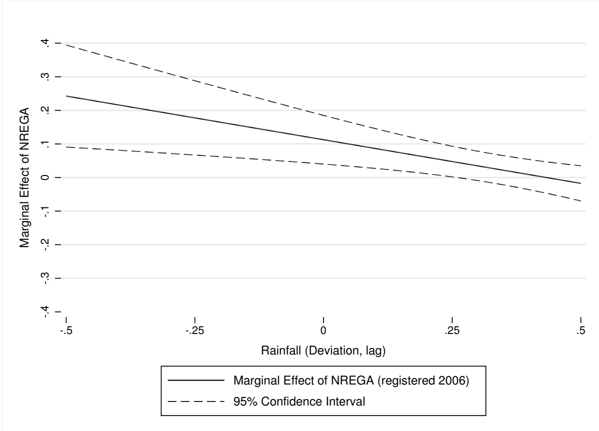
projects, crop insurance schemes or public works programmes other than the NREGS. The results are reported in the Appendix, Table B.3. I find that treatment effects are smaller in villages with existing crop insurance programmes and watershed development projects. This supports the hypothesis that the NREGS has an insurance function for households because observed effects on input allocation are smaller if households already have access to other insurance or risk mitigation mechanisms. Finally, treatment effects are very similar in villages with ongoing public work programmes and villages without such programmes. This supports the hypothesis, that it is indeed the employment guarantee that affects households' agricultural production decisions. Furthermore, I perform jacknife estimations in order to detect influential outliers, as reported in the Appendix, Table B.4. The results are robust to jacknife estimation if individual households (column 1) or villages (column 2) are excluded from the estimation. If this estimation excludes entire blocks (sub-districts), however, the standard errors increase considerably (column 3). But since the number of blocks in the sample is very small, this is not too surprising.

5.5 Heterogeneity of treatment effects

As mentioned before, the NREGS has different effects on households. This also means that households might register with the NREGS for different reasons. For some households, consumption needs are a much more important reason for registering with the programme than the insurance effect. We would thus expect households to react differently to the availability of the NREGS depending on whether the programme can contribute to smoothing their incomes in the case of a shock. Households that need to work for the NREGS as much as possible to satisfy their consumption needs - even in good years - are unlikely to cultivate higher risk crops despite working for the NREGS. In contrast, households that rely on the NREGS mainly in the case of a shock are expected to react differently. One option to separate these two groups is to condition the treatment effect on the main reason for households in the second group to register with the programme: the experience of a shock to agricultural production. Since rainfall fluctuations are among the most important risks to agricultural production, I interact the treatment variable with lagged deviation in rainfall levels. Table B.5 in the Appendix reports the results of the regression with interaction terms and displays the marginal effects of the NREGS computed at different levels of rainfall deviation.

For better visualization, the marginal effect of the NREGS conditional on lagged rainfall is plotted in Figure 4. It shows that the treatment effect is large and statistically significant for households that experienced rainfall shocks before registering with the NREGS and diminishes for households who registered despite more favourable rainfall levels. This suggests that households that registered with the NREGS to cope with a shock are much more likely to adjust their input allocation towards more profitable crops, which is exactly what we would expect in case of an insurance effect. In contrast, households that had already registered with the NREGS in 2007 even though they experienced a good year in their agricultural production do not adjust their production decisions. These are probably households that rely on the NREGS for additional income rather than as a risk-coping instrument.

Figure 4: Marginal effect of the NREGS on inputs allocated to cotton conditional on lagged rainfall



Source: Own estimation, based on Young Lives data

6 Conclusions

This paper assesses the role of uninsured risks in households' production decisions. It presents theoretical and empirical evidence that an employment guarantee, such as the NREGS in India, improves households' ability to cope with shocks in agriculture by guaranteeing income opportunities in areas where and time periods when they previously did not exist. By improving the risk management of households, the NREGS enables households to switch their production towards higher profitability products and to generate higher incomes from agricultural production. With this finding, this paper provides empirical evidence of the validity of the theory of choice under uncertainty as much as it contributes new insights to the ongoing debate on the effects of the NREGS on agricultural productivity.

The results of this paper show that public works programmes can have welfare effects that go beyond immediate income effects. The insurance effect of the NREGS on agricultural productivity is similar to the effects of rainfall insurance analysed by Karlan et al. (2012) and Cole et al. (2013). But in contrast to purchasing insurance, registration with the NREGS provides little ex ante cost. Since trust-related considerations continue to limit the uptake of insurance products in many countries, providing public works schemes - combined with an employment guarantee - could be an alternative option with which to protect households against agricultural production risks and to enable productivity gains in agriculture.

Current discussions regarding the effects of the NREGS on agricultural productivity focus mainly on the trade-off between providing minimum income to poor households, on one hand, and ensuring that production costs in the agricultural sector do not rise too drastically due to increased agricultural wages, on the other hand. As this paper shows, these discussions have failed to consider the following key aspect: because the number of workdays each household is entitled to additionally affects its risk management capacity, the amount of risk each household is willing to take - and therewith potential productivity gains - will crucially depend on the number of workdays each household can expect to be able to work in the case of production shocks. Thus, increasing the number of days each household is entitled to work with the NREGS could increase agricultural productivity - an argument that has been largely ignored so far. The assumption that only large-scale farmers can raise agricultural productivity is still a mainstream one. Including in the discussion the effects of the NREGS on households' risk management and the resulting changes in production decisions might change the overall picture.

The findings here contain some lessons for the ongoing debates on the effectiveness of the NREGS and for other countries considering the implementation of such schemes. First, for the insurance effect to unfold, the design of the public works programme is crucial. An employment guarantee that is entitled by law and entails adequate grievance redress mechanisms provides households with the necessary protection against agricultural production risks to enable them to take more risks in their production and investment decisions. Additionally, it is crucial not to severely limit the number of workdays, otherwise such a scheme's potential as a risk-coping instrument cannot be realized. Second, implementation matters. The data analysed in this paper cover only the state of Andhra Pradesh. This is, *inter alia*, because the performance of the NREGS in terms of the number of workdays generated per eligible household varies immensely across states and even across districts in India. Andhra Pradesh is one of the best performing states in the implementation of the NREGS, so it goes without saying that many of the effects captured in this paper might not be found in all Indian states. Third, working for a public works scheme is always associated with opportunity costs. In countries or regions with well functioning off-farm labour markets, providing public works schemes might not be necessary. A food-for-work programme or cash-for-work programme will always only be effective in areas and time periods where labour is in surplus.

Obviously, a number of open questions remain, and more research is required to provide conclusive answers to these questions. First, the internal and external validity of the results here could be improved with more data - especially if the analysis were extended to the whole country. Second, the effects of the programme on total levels of inputs allocated and on investments in fixed capital could prove to be very interesting topics of study. Similarly, the effects on households' willingness to engage in entrepreneurial activity need to be assessed. Third, heterogeneity in treatment effects could be assessed in more detail with more data.

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A Mathematical Appendix

A.1 Deterministic Case

In the deterministic case, the Lagrange can be summarised as follows:

$$
\begin{aligned}
\mathcal{L} =& U_1(C_1) + \delta U_2(C_2) \\
&+ \lambda(w_1(T_1 - l_1^d - l_1^s) - g(i^d + i^s) + B - C_1) \\
&+ \mu[(p - \alpha w_2^r)(Q^d + Q^s) + w_2 T_2 - (1+r)B - C_2] \\
&+ \varphi(B^m - B) \\
&+ \rho(1 - a^d - a^s)
\end{aligned}
$$

Differentiating the Lagrange with respect to the choice variables, leads to the following first order conditions:[31]

$$\frac{\partial \mathcal{L}}{\partial C_1} = \frac{\partial U_1}{\partial C_1} - \lambda = 0 \tag{A.1}$$

$$\frac{\partial \mathcal{L}}{\partial C_2} = \delta \frac{\partial U_2}{\partial C_2} - \mu = 0 \tag{A.2}$$

$$\frac{\partial \mathcal{L}}{\partial l_1^d} = -\lambda w_1 + \mu(p - \alpha w_2) \frac{\partial f^d}{\partial l_1^d} = 0 \tag{A.3}$$

$$\frac{\partial \mathcal{L}}{\partial l_1^s} = -\lambda w_1 + \mu(p - \alpha w_2) \frac{\partial f^s}{\partial l_1^s} = 0 \tag{A.4}$$

$$\frac{\partial \mathcal{L}}{\partial i^d} = -\lambda g + \mu(p - \alpha w_2^r) \frac{\partial f^d}{\partial i^d} = 0 \tag{A.5}$$

$$\frac{\partial \mathcal{L}}{\partial i^s} = -\lambda g + \mu(p - \alpha w_2^r) \frac{\partial f^s}{\partial i^s} = 0 \tag{A.6}$$

$$\frac{\partial \mathcal{L}}{\partial a^d} = \mu(p - \alpha w_2^r) \frac{\partial f^d}{\partial a^d} - \gamma = 0 \tag{A.7}$$

$$\frac{\partial \mathcal{L}}{\partial a^s} = \mu(p - \alpha w_2^r) \frac{\partial f^s}{\partial a^s} - \gamma = 0 \tag{A.8}$$

$$\frac{\partial \mathcal{L}}{\partial B} = \lambda - \mu(1+r) - \varphi = 0 \tag{A.9}$$

Rearranging the first order conditions (A.1) and (A.2) gives:

$$\lambda = \frac{\partial U_1}{\partial C_1} \tag{A.10}$$

$$\mu = \delta \frac{\partial U_2}{\partial C_2} \tag{A.11}$$

[31] Remember that $Q^d = f^d(a^d, l_1^d, i^d)$ and $Q^s = f^s(a^s, l_1^s, i^s)$.

And including (A.10) and (A.11) into (A.3)-(A.9) gives our decision rules:

$$w_1\frac{\partial U_1}{\partial C_1}-(p-\alpha w_2^r)\delta\frac{\partial U_2}{\partial C_2}\frac{\partial f^d}{\partial l_1^d}=0\Leftrightarrow\frac{\partial f^d}{\partial l_1^d}=\frac{w_1}{(p-\alpha w_2^r)}\frac{\frac{\partial U_1}{\partial C_1}}{\delta\frac{\partial U_2}{\partial C_2}} \tag{A.12}$$

$$w_1\frac{\partial U_1}{\partial C_1}-(p-\alpha w_2^r)\delta\frac{\partial U_2}{\partial C_2}\frac{\partial f^s}{\partial l_1^s}=0\Leftrightarrow\frac{\partial f^s}{\partial l_1^s}=\frac{w_1}{(p-\alpha w_2^r)}\frac{\frac{\partial U_1}{\partial C_1}}{\delta\frac{\partial U_2}{\partial C_2}} \tag{A.13}$$

$$g\frac{\partial U_1}{\partial C_1}-(p-\alpha w_2^r)\delta\frac{\partial U_2}{\partial C_2}\frac{\partial f^d}{\partial i^d}=0\Leftrightarrow\frac{\partial f^d}{\partial i^d}=\frac{g}{(p-\alpha w_2^r)}\frac{\frac{\partial U_1}{\partial C_1}}{\delta\frac{\partial U_2}{\partial C_2}} \tag{A.14}$$

$$g\frac{\partial U_1}{\partial C_1}-(p-\alpha w_2^r)\delta\frac{\partial U_2}{\partial C_2}\frac{\partial f^s}{\partial i^s}=0\Leftrightarrow\frac{\partial f^s}{\partial i^s}=\frac{g}{(p-\alpha w_2^r)}\frac{\frac{\partial U_1}{\partial C_1}}{\delta\frac{\partial U_2}{\partial C_2}} \tag{A.15}$$

$$\frac{\partial f^d}{\partial a^d}=\frac{\partial f^s}{\partial a^s} \tag{A.16}$$

$$\varphi=\frac{\partial U_1}{\partial C_1}-\delta(1+r)\frac{\partial U_2}{\partial C_2} \tag{A.17}$$

A.2 Stochastic Case

When introducing uncertainty, the Lagrange becomes the following:

$$\begin{aligned}\mathcal{L}=&U_1(C_1)+\lambda(w_1(T_1-l_1^d-l_1^s)-g(i^d+i^s)+B-C_1))\\&+E[\delta U_2(C_2)+\mu[(p-\alpha w_2^r)(Q^d+Q^s)+w_2T_2-(1+r)B-C_2]]\\&+\varphi(B^m-B)\\&+\rho(1-a^d-a^s)\end{aligned}$$

Note here that the household forms expectations not only about the utility he derives from consumption in period 2, but also about the level of consumption that can be achieved. Differentiating the Lagrange with respect to the choice variables, leads to the following first order conditions:[32]

$$\frac{\partial \mathcal{L}}{\partial C_1} = \frac{\partial U_1}{\partial C_1} - \lambda = 0 \tag{A.18}$$

$$\frac{\partial \mathcal{L}}{\partial C_2} = E[\delta \frac{\partial U_2}{\partial C_2} - \mu] = 0 \tag{A.19}$$

$$\frac{\partial \mathcal{L}}{\partial l_1^d} = -\lambda w_1 + E[\mu](p - \alpha w_2^r)\frac{\partial f^d}{\partial l_1^d} = 0 \tag{A.20}$$

$$\frac{\partial \mathcal{L}}{\partial l_1^s} = -\lambda w_1 + E[\mu(p - \alpha w_2^r)\epsilon \frac{\partial f^s}{\partial l_1^s}] = 0 \tag{A.21}$$

$$\frac{\partial \mathcal{L}}{\partial i^d} = -\lambda g + E[\mu](p - \alpha w_2^r)\frac{\partial f^d}{\partial i^d} = 0 \tag{A.22}$$

$$\frac{\partial \mathcal{L}}{\partial i^s} = -\lambda g + E[\mu(p - \alpha w_2^r)\epsilon \frac{\partial f^s}{\partial i^s}] = 0 \tag{A.23}$$

$$\frac{\partial \mathcal{L}}{\partial a^d} = E[\mu](p - \alpha w_2^r)\frac{\partial f^d}{\partial a^d} - \gamma = 0 \tag{A.24}$$

$$\frac{\partial \mathcal{L}}{\partial a^s} = E[\mu(p - \alpha w_2^r)\epsilon \frac{\partial f^s}{\partial a^s}] - \gamma = 0 \tag{A.25}$$

$$\frac{\partial \mathcal{L}}{\partial B} = \lambda - E[\mu](1 + r) - \varphi = 0 \tag{A.26}$$

Rearranging (A.18) and (A.19) gives:

$$\lambda = \frac{\partial U_1}{\partial C_1} \tag{A.27}$$

$$E[\mu] = \delta \frac{\partial EU_2}{\partial C_2} \tag{A.28}$$

And the optimal consumption rule becomes:

$$\frac{\partial U_1}{\partial C_1} = (1 + r)\delta \frac{\partial EU_2}{\partial C_2} + \varphi \tag{A.29}$$

Including (A.27) and (A.28) into (A.20)-(A.25) gives our decision rules for l_1^d,

$$w_1 \frac{\partial U_1}{\partial C_1} - (p - \alpha w_2^r)\delta \frac{\partial EU_2}{\partial C_2}\frac{\partial f^d}{\partial l_1^d} = 0$$

$$\Leftrightarrow \frac{\partial f^d}{\partial l_1^d} = \frac{w_1}{(p - \alpha w_2^r)} \frac{\frac{\partial U_1}{\partial C_1}}{\delta \frac{\partial EU_2}{\partial C_2}} \tag{A.30}$$

[32] Remember that $Q^d = f^d(a^d, l_1^d, i^d)$ and $Q^s = \epsilon f^s(a^s, l_1^s, i^s)$.

for l_1^s,

$$\begin{aligned}
& w_1 \frac{\partial U_1}{\partial C_1} - (p - \alpha w_2^r) \frac{\partial f^s}{\partial l_1^s} \delta E[\frac{\partial U_2}{\partial C_2} \epsilon] = 0 \\
& \Leftrightarrow (p - \alpha w_2^r) \frac{\partial f^s}{\partial l_1^s} \delta [\frac{\partial EU_2}{\partial C_2} E[\epsilon] + cov(\frac{\partial U_2}{\partial C_2}, \epsilon)] = w_1 \frac{\partial U_1}{\partial C_1} \\
& \Leftrightarrow \frac{\partial f^s}{\partial l_1^s} = \frac{w_1}{(p - \alpha w_2^r)} \frac{\frac{\partial U_1}{\partial C_1}}{\delta \frac{\partial EU_2}{\partial C_2}} - \frac{cov(\frac{\partial U_2}{\partial C_2}, \epsilon)}{(p - \alpha w_2^r) \delta \frac{\partial EU_2}{\partial C_2}}
\end{aligned} \tag{A.31}$$

for i^d,

$$\begin{aligned}
& g \frac{\partial U_1}{\partial C_1} - (p - \alpha w_2^r) \delta \frac{\partial EU_2}{\partial C_2} \frac{\partial f^d}{\partial i^d} = 0 \\
& \Leftrightarrow \frac{\partial f^d}{\partial i^d} = \frac{g}{(p - \alpha w_2^r)} \frac{\frac{\partial U_1}{\partial C_1}}{\delta \frac{\partial EU_2}{\partial C_2}}
\end{aligned} \tag{A.32}$$

for i^s,

$$\begin{aligned}
& g \frac{\partial U_1}{\partial C_1} - (p - \alpha w_2^r) \frac{\partial Q^s}{\partial i^s} \delta E[\frac{\partial U_2}{\partial C_2} \epsilon] = 0 \\
& \Leftrightarrow (p - \alpha w_2^r) \frac{\partial f^s}{\partial i^s} \delta [\frac{\partial EU_2}{\partial C_2} E[\epsilon] + cov(\frac{\partial U_2}{\partial C_2}, \epsilon)] = g \frac{\partial U_1}{\partial C_1} \\
& \Leftrightarrow \frac{\partial f^s}{\partial i^s} = \frac{g}{(p - \alpha w_2^r)} \frac{\frac{\partial U_1}{\partial C_1}}{\delta \frac{\partial EU_2}{\partial C_2}} - \frac{cov(\frac{\partial U_2}{\partial C_2}, \epsilon)}{(p - \alpha w_2^r) \delta \frac{\partial EU_2}{\partial C_2}}
\end{aligned} \tag{A.33}$$

for a^d,

$$\delta \frac{\partial EU_2}{\partial C_2} (p - \alpha w_2^r) \frac{\partial f^d}{\partial a^d} = \gamma$$

and a^s,

$$\begin{aligned}
& (p - \alpha w_2^r) \frac{\partial f^s}{\partial a^s} \delta E[\frac{\partial U_2}{\partial C_2} \epsilon] = \gamma \\
& \Leftrightarrow (p - \alpha w_2^r) \frac{\partial f^s}{\partial a^s} \delta \frac{\partial EU_2}{\partial C_2} E[\epsilon] + cov(\frac{\partial U_2}{\partial C_2}, \epsilon) = \gamma
\end{aligned}$$

resulting in:

$$\frac{\partial f^s}{\partial a^s} = \frac{\partial f^d}{\partial a^d} - \frac{cov(\frac{\partial U_2}{\partial C_2}, \epsilon)}{(p - \alpha w_2^r) \delta \frac{\partial EU_2}{\partial C_2}} \tag{A.34}$$

B Tables

Table B.1: District-level statistics

		Treatment	Control
GDP per capita (2006-07)		783487	776179.5
Rural population (2001 census)		80.54	84.64
SC/ST population (2001 census)		20.50	18.36
Literacy rate (2001 census)		54.6	64.4
Cropping Intensity (2007-08)		1.238	1.505
Avr. wage rate agric. labourers (2007)	Men	70.26	82.92
	Women	54.91	57.23

Source: Districts at a glance, Directorate of Economics & Statistics, Govt. of Andhra Pradesh

Table B.2: Inputs allocated to Cotton in Phase I districts (Fixed Effects)

	(1)	(2)
Cumulative expend. NREGS (April 2008, log)	0.108***	
	(0.030)	
Persondays per job card NREGS (FY 2007/08)		0.008***
		(0.002)
Variable inputs (log)	0.089***	0.092***
	(0.023)	(0.024)
Area cultivated (acres, log)	-0.014	-0.017
	(0.011)	(0.011)
Irrigated area (% of total)	-0.084**	-0.089***
	(0.026)	(0.025)
Annual income, off-farm activities (log)	-0.010	-0.011
	(0.006)	(0.006)
Wealth index	-0.063	-0.056
	(0.094)	(0.093)
Rainfall (deviation, lag)	-0.160	-0.170
	(0.090)	(0.090)
Year 2009 (dummy)	-0.528**	-0.008
	(0.187)	(0.073)
Observations	1538	1538

Clustered standard errors in parentheses.

Region-year dummies and self reported shocks included, but not reported.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.3: Interaction with previously existing programmes (Fixed Effects)

	Crop insurance		Watershed dev.		Public works	
	(1)	(2)	(1)	(2)	(1)	(2)
NREGS introduced in district	0.116**		0.105**		0.100*	
	(0.040)		(0.035)		(0.043)	
NREGS#Crop insurance	-0.056					
	(0.036)					
NREGS#Watershed dev.			-0.039			
			(0.029)			
NREGS#Public works					-0.012	
					(0.035)	
Controls	Yes		Yes		Yes	
Year dummy	Yes		Yes		Yes	
Marginal effect of NREGS introduced in district						
at gov. program = 0		0.116**		0.105**		0.100*
		(0.040)		(0.034)		(0.043)
at gov. program = 1		0.060^{+}		0.066*		0.087**
		(0.033)		(0.033)		(0.029)
Observations	2228		2228		2228	

Clustered standard errors in parentheses.
Marginal effects in second column.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.4: Results of jacknife estimation

	Household	Village	Mandal
NREGS introduced in district	0.099***	0.099**	0.099
	(0.017)	(0.036)	(0.091)
Observations	2236	2236	2236

Jacknife standard errors in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.5: Effect of NREGS conditional on lagged rainfall (Fixed Effects)

	All districts		Phase I districts	
	(1)	(2)	(1)	(2)
NREGS registered (2007)	0.144***		0.112**	
	(0.039)		(0.037)	
NREGS#Rainfall	-0.314**		-0.259**	
	(0.097)		(0.090)	
Controls	Yes		Yes	
Year dummy	Yes		Yes	
Marginal effect of NREGS registered (2007)				
at Rainfall (dev., lag)= -0.5		0.301***		0.242**
		(0.084)		(0.078)
at Rainfall (dev., lag)= -0.4		0.269***		0.216**
		(0.074)		(0.069)
at Rainfall (dev., lag)= -0.3		0.238***		0.190**
		(0.065)		(0.061)
at Rainfall (dev., lag)= -0.2		0.206***		0.164**
		(0.056)		(0.053)
at Rainfall (dev., lag)= -0.1		0.175***		0.138**
		(0.047)		(0.045)
at Rainfall (dev., lag)= 0		0.144***		0.112**
		(0.039)		(0.037)
at Rainfall (dev., lag)= 0.1		0.112**		0.087**
		(0.031)		(0.030)
at Rainfall (dev., lag)= 0.2		0.081***		0.061*
		(0.025)		(0.025)
at Rainfall (dev., lag)= 0.3		0.049*		0.035
		(0.022)		(0.022)
at Rainfall (dev., lag)= 0.4		0.018		0.009
		(0.023)		(0.023)
at Rainfall (dev., lag)= 0.5		-0.013		-0.017
		(0.027)		(0.027)
Observations	2236	2236	1538	1538

Clustered standard errors in parentheses.

Coefficients in first and marginal effects in second column.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$