Risk, Insurance and Wages in General Equilibrium

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October 2014

Abstract

We estimate the general-equilibrium labor market effects of a randomized control trial in which a rainfall index insurance product was marketed to both cultivators and agricultural wage laborers in India. Consistent with the theoretical predictions of a general-equilibrium model of wage setting with weather risk, we find that both labor demand and equilibrium wages become more rainfall sensitive when cultivators are offered rainfall insurance, because insurance induces cultivators to switch to riskier, higher-yield production methods. The same insurance contract offered to agricultural laborers smoothes wages across rainfall states by reducing labor supply during droughts (when insurance payouts occur). Policy simulations based on our estimates suggest that selling insurance only to land-owning cultivators (which is the current regulatory practice in India and other developing countries) makes wage laborers worse off in some states of the world due to the increase in wage volatility, relative to a situation where insurance does not exist at all. Marketing insurance to both cultivators and the landless eliminates this adverse effect on the landless, and mildly increases average wages compared to a regime of no insurance.

JEL Codes: O16, O13

Keywords: Index insurance, Agricultural Wages, General Equilibrium Effects

* We thank USAID/BASIS at UC-Davis, the DFID/LSE/Oxford *International Growth Centre*, and the Macmillan Center at Yale University for financial support. We thank the *Centre for Microfinance* at IFMR (Chennai, India), Hari Nagarajan at the *National Council of Applied Economic Research* (Delhi, India), and the *Agricultural Insurance Company of India, Lombard* (especially Mr. Kolli Rao) for their collaboration in fieldwork and program implementation. Lisa Nestor managed all aspects of the fieldwork extremely well. Laura Feeney provided excellent research assistance. Michael Carter, Judy Chevalier, Seema Jayachandran, Kaivan Munshi, Duncan Thomas, Chris Udry, Juanjuan Zhang and seminar participants at the 27th BREAD conference, Harvard/MIT Development Seminar, University of Michigan, Cambridge University, IFPRI, UC-Davis BASIS Workshop, Yale University China and India Customer Insights Conference, Vanderbilt University, 2013 Arizona State Conference on Development of Human Capital, and 2013 HKUST Conference on Human Resources and Economic Development provided valuable comments.

1. Introduction

Field experiments providing weather insurance to farmers find, consistent with economic theory, that formerly uninsured farmers switch towards riskier, but higher-yield, crop varieties (Cole et al 2013b; Mobarak and Rosenzweig 2014), thus making agricultural output higher but more rainfall-sensitive (Karlan et al 2014; Mobarak and Rosenzweig 2013). Most cultivators hire landless laborers for harvest tasks. Cultivator risk-taking (when they are insured) can therefore change labor demand and make wage rates more volatile, potentially worsening the welfare of laborers, who make up a sizeable proportion of the world's impoverished population. On the other hand, if risk-taking increases average yields, then average wages may rise. To properly evaluate the welfare effects of introducing a formal insurance product, it is important to move beyond effects on the treated population, and determine the general-equilibrium effects on both wage levels and volatility.

Is there reason to think that the provision of insurance to cultivators could make the landless worse off? There is direct evidence that insurance induces cultivators to choose technologies that lower output under adverse conditions compared with the uninsured. In Mobarak and Rosenzweig (2014) we show that offering an index insurance product to rice farmers in Tamil Nadu (a subset of our sample that we examine here) reduced the fraction of cultivated acreage planted with rice varieties rated 'good' for drought resistance and increased the acreage for rice varieties rated 'good' for yield (9%). Cole *et al.* (2013b) also report evidence of a direct switch to high return but more-rainfall sensitive cash crops by insured farmers in India. There is also evidence that output is lower under adverse weather conditions when farmers are insured. Karlan *et al.* (2014) show that a sample of Ghanaian farmers who were randomly offered free index insurance experience $157 greater output per millimeter of additional rainfall relative to an uninsured control group, but that during a drought, output is over a thousand dollars *less* among the insured. In our sample of cultivators, described below, we find a similar result. Figure 1 plots the relationship between farm output value and rainfall for our sample of Indian farmers stratified by whether or not they were offered the rainfall insurance product. Output becomes more sensitive to rainfall for insured farmers, and output is actually lower for the insured than the uninsured in the lower half of the rainfall distribution. We might expect therefore that harvest labor demand is also lower in the low state for the insured cultivators.

In this paper we examine general-equilibrium labor market effects using a large-scale randomized controlled trial (RCT) that marketed rainfall insurance to both landless and cultivating households in rural India. We estimate the effects of insurance on agricultural labor supply, *ex ante* and *ex post* labor demand, and equilibrium wages. The labor-market spillover effects on the landless are of direct policy relevance because in India and other developing countries, agricultural insurance is explicitly targeted to only those with an "insurable interest" – i.e., cultivators with land.[1] Income of the landless is arguably even more directly tied to rainfall[2], and precluding the landless from the insurance market prevents the poorest segment of society from using insurance to smooth consumption. Further, our analysis shows that selling insurance *only* to cultivators, as is the current de-facto policy in India, can make the landless worse off via general-equilibrium wage effects, compared to a regime of no insurance.[3]

Comprehensive evaluation of any potential development program requires an accounting of general-equilibrium changes, especially to assess potential effects when the program is scaled up (Acemoglu 2010, Heckman 1991; Rodrik 2009). A number of RCT's have identified beneficial effects on the treated from various interventions, but few have examined the general-equilibrium

[1] These products are regulated like conventional indemnity insurance, and the insurable interest requirement is typically interpreted as a cultivation requirement for agricultural insurance.

[2] Heterogeneity in land and landowner characteristics introduces some idiosyncratic component of risk for cultivators, whereas all agricultural laborers of the same gender face the same wage rate.

[3] We marketed rainfall index insurance (a contract which pays out if the monsoon is delayed) to both cultivators and landless agricultural wage workers in the same villages, in order to study both the labor demand and the labor supply responses to insurance sales. Our partnership with the Agricultural Insurance Company of India (AICI), the largest state insurer, allowed us to circumvent the regulatory restriction against marketing insurance to agricultural laborers.

consequences for the beneficiaries and non-beneficiaries that emanate from aggregate price changes induced by programs implemented on a large scale. For example, providing better education and training opportunities to large numbers of beneficiaries (Banerjee *et al.* 2007; Blattman *et al.* forthcoming) may change skilled wages, improving migration opportunities (Bryan *et al.* 2013) may change wages at the destination, and providing livestock assets on a large scale (Bandiera *et al* 2013) may affect livestock prices. A number of RCT's have considered non-market spillovers from interventions on the non-treated. These include health externalities (Miguel and Kremer 2004), financial transfers (Angelucci and DeGiorgi 2009), and social learning in technology adoption (Kremer and Miguel 2007, Oster and Thornton 2012, Miller and Mobarak 2013). A distinguishing characteristic of our study is that the spillovers we identify work through the aggregate effects of equilibrium price changes that are the consequence of any scaled-up intervention.[4]

Our research contributes to a burgeoning literature on the effects of insurance marketed through RCT's[5] by tracking the labor market spillovers of such interventions using a general-equilibrium model. Our research also contributes to a sparse but important literature on the determinants of rural wages in developing countries. The relative dearth of literature on the determinants of the price of labor can be traced back to "surplus labor" models from the 1960s (Lewis 1968; Ranis and Fei 1961) which posited that wages are set institutionally, rather than through economic forces. Important subsequent contributions to this literature include nutrition-based efficiency wage models (Mazumdar 1959; DasGupta and Ray 1986), wage determination assuming complete markets (Rosenzweig 1978), and nominal wage rigidity with uninsured shocks (Kaur 2012). Our work builds on Jayachandran (2006), who showed that credit market

[4] Crepon *et al.* 2012 and Muralidharan and Sundararaman (2013) study aggregate effects in relevant markets, but do not estimate price or (teacher) wage effects. There are related non-experimental studies of general equilibrium effects of credit market imperfections on wages (Jayachandran 2006) and on technology diffusion and price dispersion (Jensen 2007, Aker 2010).

[5] Gine and Yang (2009), Cai *et al.* (2009), Carter *et al.* 2011, Cai *et al.* (2012), Cole *et al.* (2013a), Cole *et al.* (2013b), Chantarat *et al.* (2013).

imperfections have general-equilibrium effects on rural wage levels and volatility that work through labor supply and migration channels. Here, we focus on uninsured risk.[6] A key innovation is that we test a model of risk and the labor market using variation derived entirely from a randomized field experiment large enough to detect general-equilibrium effects. Use of randomized variation limits concerns about omitted variables bias and other threats to identification. The experimental design also allows us to examine the precise labor supply and labor demand mechanisms by which insurance affects wages.

Our model provides implications for the effects of insurance on the labor demand and supply responses of cultivators and agricultural wage laborers who face rainfall risk, which in turn affect wages in market equilibrium. The empirical tests are based on randomized offers of a rainfall insurance contract to individual landless laborers and cultivators, variation in the *fractions* of cultivators or laborers in a village receiving offers, and variation in the occurrence of insurance payouts. We separately estimate a labor demand equation for landowning cultivators, a labor supply equation for landless workers, and a general-equilibrium wage equation. We use these estimates to analyze changes in equilibrium wage profiles under three policy relevant scenarios: a) when only cultivators are offered insurance, b) when both cultivators and laborers are targeted and c) where only laborers are targeted with insurance marketing. These counterfactual policy simulations are conducted within the bounds of our data because we have significant variation in both the proportion of cultivators and the proportion of agricultural labor households who receive insurance marketing across our sample villages.

Consistent with the theoretical predictions, we find that insured cultivators take more risk, and harvest labor demand becomes more rainfall-sensitive. In particular, insured cultivators use

[6] In our model, we assume complete credit markets to highlight the risk channel and later show that our empirical results are robust to controlling for the effects of credit market imperfections, using the same set of proxies used in Jayachandran (2006).

more harvest labor when rainfall is ample but use less labor in low-rainfall conditions compared with uninsured cultivators. On the other hand, insured agricultural wage workers supply less labor when insurance payouts occur. In villages that qualified for a payout, the insured are less likely to participate in the agricultural labor market compared to the uninsured, and they supply fewer hours conditional on participating. This implies that insuring a subset of wage workers indirectly insures other (uninsured) wage workers in the village through the labor supply choices of the insured.

These labor demand and labor supply responses propagate through to general-equilibrium wage effects. Agricultural wages become more sensitive to rainfall when a larger fraction of cultivators in the village are offered insurance (the labor demand channel), with wages lower when rainfall is low and higher when rainfall is high. Wages are, however, higher when rainfall is low when a larger fraction of laborers are offered insurance in villages that ultimately qualified for a payout (the labor supply effect). Policy simulations based on our estimates suggest that risk-averse landless wage workers could be worse off if insurance were only marketed to cultivators, *even relative to a case where rainfall insurance is never introduced to anyone in the village at all,* due to the increase in wage volatility and the reduction in wages during droughts. Symmetrically, marketing insurance to landless workers helps smooth wages across rainfall realizations in villages where payouts occur (inducing the labor supply response), which makes risk-averse cultivators worse off. The opposing labor demand and labor supply effects evidently cancel each other when insurance is marketed to both cultivators and wage workers in our simulation, and the net effect is a slight increase in equilibrium wages during periods of high rainfall.

The next section presents the model of the agricultural labor market. A description of the experimental design and a description of the data follow, after which we present the estimates of the individual effects of insurance provision on labor demand and supply, aggregate effects on equilibrium wages, and counterfactual policy simulations based on these estimates. Finally, we discuss implications for policy and future research in a brief conclusion.

2. A Model of Insurance and the Agricultural Labor Market

2.1 Landless labor households, labor supply and rainfall insurance

To highlight the role of risk in determining equilibrium wages we set out a simple model of the agricultural labor market. We consider two groups – cultivators, who own land and hire labor but do not supply labor, and the landless, who supply labor to cultivators. In India the landless almost never lease in land and cultivate. Smaller landowners who cultivate sometimes also supply agricultural labor, and our main results are unaffected by allowing cultivators to also supply labor. The key assumption is that cultivators are net hirers of labor. A second simplification is that to make the effects of risk transparent we employ a one-period (one-season) model for laborers (cultivators) and thus we ignore the multi-period smoothing problem highlighted by Jayachandran (2006) that arises due to credit constraints. Agents would self-insure through savings in a multi-period model, so credit constraints would have to play a role in addition to uninsured risk in a more general model.[7]

We begin with the labor supply decision made by the landless. Each landless household is endowed with non-earnings income m and one unit of time. Utility functions are Cobb-Douglas in leisure h and consumption c:

$$U = h^{\gamma} c^{(1-\gamma)}$$

Rainfall θ^{j} can be either low (L) or high (H), and $j = H \text{ or } L$ denotes the state of nature. The L-state occurs with probability q. We consider two groups of landless, corresponding to our

[7] In the empirical work we allow for credit constraints, adding to our equilibrium wage specification the same variables used by Jayachandran (2006) in her tests of credit constraints. We find evidence of credit constraints consistent with Jayachandran (2006). We also carry out a test for within-season credit constraints on cultivator harvest labor demand.

RCT – one group which is able to purchase insurance optimally at an offered price *p* per unit (the insured), and those for whom insurance is not offered or available. Insurance pays out *I* in the low state of nature *L*. Thus, consumption in the two states for households that purchase insurance is

$$c^L = w^L(1-h) + m - pI + I$$

$$c^H = w^H(1-h) + m - pI$$

where $1 - h = l_s$ is labor supply. The landless household maximizes expected utility

$$\text{Max}_{I,h}\, E(U) = qU^L + (1-q)U^H,$$

and the FONC is $$q(1-p)U_c^L = p(1-q)U_c^H$$ (U_c^L=U_c^H if actuarially fair.)

Solving for labor supply in each realized state j, we get that $l_s^j = 1 - \gamma - \gamma\frac{y^j}{w^j}$,where y^j is non-earnings income in state j, inclusive of the cost of and payout from insurance. This leads to the following proposition:

Proposition 1: The labor supply of the insured and uninsured will differ depending on the weather state:

a. *In the low state, the labor supply of the insured will be lower than that of the uninsured.*

b. *In the high state, the labor supply of the insured will be higher than that of the uninsured.*

The proof is given in Table 1, which provides the labor supplied in the two states for the insured and uninsured landless. In the low state *L*, where there are insurance payouts, the non-earnings income of the insured is greater than that of the uninsured because of the payouts. Labor supply of the insured is thus lower than that of the uninsured, because leisure is a normal good. In the high-state *H*, where there are no payouts, the net income of the insured is lower than the uninsured, by the amount they paid for the insurance contract, and thus they work more than the uninsured.[8]

[8] To ensure sufficient insurance take-up, the insurance premium was heavily subsidized in our RCT. We therefore do not expect much of an income effect in state *H* from our intervention. Insurance payouts were

2.2 Cultivator households, the demand for labor and rainfall insurance

Cultivators are endowed with one unit of land and non-earnings income *m*. Production takes place in two stages. In stage 2, the state of nature θ^j is realized, labor is hired and profits are maximized. Cultivator and landless households can freely save (at a fixed interest rate *r*) and borrow within the agricultural cycle. Stage-2 output q^j in state j is given by

$$q^j = (1-\alpha) + \alpha\theta^j,$$

$$\text{where } \theta^j = 0 \text{ in the L state}$$

$$= \mu \text{ in the H state, with } \mu > 1.$$[9]

In stage 1 (planting stage), cultivators decide on the stage-1 technology α, choosing between the most conservative, lowest-yielding technology ($\alpha = 0$), whereby output is independent of the state of nature, and the most profitable, in terms of expected value, but riskiest technology ($\alpha = 1$).[10] They also decide whether to buy insurance. Labor demand in the second stage is Leontief, with δ units of labor required per unit of output. Thus, in any state j, second-stage (harvest) labor demand is a function of the state of nature and of the technology chosen in stage 1. It is easy to see that labor demand is higher on average but will be more sensitive to weather realizations the higher is α.

large when they occur, however, and our empirical exercise will therefore concentrate on labor supply effects in villages that qualified for a payout.

[9] We are grateful to Catherine de Fontenay of the Melbourne Business School for suggesting this technology specification.

[10] We ignore the use of labor in the first (planting) stage, as we will focus the empirical work on the demand for and supply of labor after the realization of the state of nature. The effect of insurance on labor demand in the first (planting) stage will solely depend on the relationship between α and labor in that stage. If α reflects seed type, for example, it is unlikely that planting-stage labor demand will be strongly affected. As we show below, there is evidently little effect of insurance provision to cultivators on the demand for planting-stage labor.

In particular, labor demand (output) will be higher in the high state but lower in the low state the higher is α.[11]

The stage-1 program is:

$$\max_{\alpha,I} E(U) = U(c_1) + b[qU(c_2^L) + (1-q)U(c_2^H)]$$

$$c_1 = m - s - pI$$

$$c_2^j = rs + [(1 + \alpha(\theta^j - 1)][p - \delta w^j] + i^L I$$

where i^L is an indicator variable for the low state, when the insurance payout occurs, s=savings, r=savings returns, and p=the output price.

It is easy to show, and is a standard result, that in the absence of insurance the amount of α < 1; that is, the technology choice α is more conservative relative to the choice that maximizes expected profits ($\alpha = 1$), and that α increases as the cost of insurance falls; i.e., insured cultivators take more risk than uninsured cultivators, consistent with the recent RCT evidence. This follows from the fact that purchasing insurance decreases cultivator marginal utility in the low state while increasing α decreases marginal utility in the high state. Given the stage-2 output (labor demand) function above, this means that the effect on the demand for labor from changes in θ^j is stronger the lower is the cost of insurance, with labor demand lower (higher) in the bad (good) state compared with the case where there is no insurance. Our empirical exercise will therefore compare the sensitivity of stage-2 (harvest stage) labor demand to rainfall variation and labor demand in above- and below-average rainfall states across insured and uninsured cultivators.

[11] This latter result is specific to the technology we have assumed, which is consistent with the emerging RCT evidence that insured farmers choose seed portfolios that are higher-yielding but less resistant to drought. It is possible that with other functional forms the provision of insurance will lead to higher planting-stage investments, and thus in all states of nature labor demand will be higher. One such technology is Cobb-Douglas. In that case, we can show that labor demand and equilibrium wages also become more sensitive to weather as insurance coverage increases, but labor demand is never lower compared with the uninsured state. Our empirical results below on labor demand and equilibrium wages reject this technology.

2.3. Labor market equilibrium

If there are *N* landless households supplying labor and *M* cultivators in the labor market then in any rainfall state *j*, we have the equilibrium condition

$$[1-\gamma-\frac{\gamma y^j}{w^j}]N = \delta[1+\alpha(\theta^j\ -1)]M$$

so that, $$w^j = M\gamma y^j/N[1-\gamma-\delta[1\ +\ \alpha(\theta^j\ -1)]]$$

We now can derive propositions for how making rainfall insurance exclusively available to either the landless or cultivators affects (a) average wages, and (b) equilibrium wage volatility Δw, which is the difference between equilibrium wages in the high and low states.

Proposition 2: *Offering insurance to landless laborers dampens wage volatility.*

Proof: The effect of an increase in non-earnings income *y* on the equilibrium wage is always positive:

$$\frac{dw^L}{dy} = M\gamma/N[1-\gamma-\delta(1-\alpha)] > 0, \text{ for } w^L > 0$$

$$\frac{dw^H}{dy} = M\gamma/N[1-\gamma-\delta(1+\ \alpha(\mu-1))] > 0, \text{ for } w^H > 0$$

From Table 1, y is higher (labor supply is lower) in state L because of the insurance payouts when the landless are insured, so w^L increases compared to the case where no landless are insured. In state H, y is lower when the landless are insured (l_s higher) than if there were no rainfall insurance because of the cost of the insurance premium, so that w^H decreases compared to the non-insurance case. The general-equilibrium effect of offering insurance to landless households thus reduces wage risk. If only some landless households purchase insurance, then income is smoothed across the states of nature for the uninsured landless. Note that by symmetry, the welfare of risk-averse cultivators decreases when the landless are able to purchase weather insurance. Profits are decreased in the low state when laborers are offered insurance (since w^L increases), and greater in the high state, due to the general-equilibrium wage effects.

<u>Proposition 3:</u> *Offering insurance to cultivators increases wage volatility and makes the landless worse of in the* L *state.*

Proof: Insured cultivators choose a higher-α technology. The effect of an increase in α on wages in the H state is positive; the effect of an increase in α on wages in the L state is negative:

$$\frac{dw^L}{d\alpha} = -M\delta\gamma y/N[1-\gamma-\delta(1-\alpha)]^2 < 0$$

$$\frac{dw^H}{d\alpha} = -M(\mu-1)\delta\gamma y/N[1-\gamma-\delta(1+\alpha(\mu-1))]^2 > 0$$

Offering insurance only to cultivators increases wage volatility and worsens the welfare of the (uninsured) landless in bad weather states.[12] On the other hand, it may also provide some benefits to the landless:

<u>Proposition 4:</u> *Offering insurance to cultivators increases average wages.*

Proof: Insured cultivators choose a higher-α technology. The effect of an increase in α on the expected equilibrium wage is positive.

$$\frac{dE(w)}{d\alpha} = M\delta\gamma E(y)[(1-q)\mu-1]/N[1-\gamma-\delta(1+\ \alpha(1-q)\mu-1)])]^2 > 0$$

To summarize, offering insurance to landless workers dampens wage volatility, because insured workers supply less labor than the uninsured when the rainfall is low (i.e. when they receive insurance payouts) and supply more labor (if they pay the full cost of insurance) when rainfall is ample. On the other hand, offering insurance to cultivators increases risk-taking, and thus makes labor demand on average higher but more volatile across rainfall states, and, given the technology

[12] Just as the uninsured landless benefit from the insured landless via general-equilibrium wage effects, risk-averse cultivators who do not have insurance benefit from the behavior of their insured counterparts: profits are higher in the low state compared to the case where no cultivator insurance is available.

specified in the model, which is consistent with observations on seed choice by insured farmers, makes the landless worse off in the low-rainfall states.

3. Experimental Design

3.1 Sampling

In 2006 the National Council of Applied Economic Research (NCAER) conducted a comprehensive listing of all rural households residing in 202 sampled villages in 17 major Indian states as part of the 2006 Rural Economic and Development Survey (REDS). That survey also provides for each village a monthly time-series of rainfall from 1999-2006 and information on soil properties. The 2006 REDS listing for three large states (Andhra Pradesh, Uttar Pradesh and Tamil Nadu) served as the sampling frame from which we drew the sample for our randomized controlled trial (RCT) marketing rainfall insurance. The 2006 REDS listing contained occupation data, and we included in our sample only cultivator households (i.e. those households owning land and whose head's primary occupation was cultivator) typically hiring in labor and "pure" agricultural labor households (households purely reliant on agricultural wages, with no member engaged in cultivation as either a primary or secondary occupation).

We collected data in 46 REDS villages in the three states, and randomly selected 42 of those villages for insurance marketing. We randomized insurance offers to households within these 42 villages in two steps: First, we randomly selected 93 of the 118 'large' castes resident in these villages.[13] Second, we randomized insurance offers at the individual level within these 93 treatment castes. Because insurance was ultimately randomized at the individual level within caste-village groupings, we therefore cluster all standard errors by caste-village (and include both village fixed

[13] The two step randomization using caste was due to a companion paper (Mobarak and Rosenzweig 2014) in which we study the effects of informal caste-based risk sharing on formal index insurance demand. We selected 'large' castes (with more than 50 members) for our sampling frame in order to precisely estimate caste-level risk sharing parameters in that paper. We will control for caste fixed effects in the labor demand and supply estimation in this paper to account for any variation in behavior across castes.

effects and caste fixed effects wherever possible). We targeted 2400 cultivators and 2400 landless laborers for insurance marketing.

3.2 The Index Insurance Marketing Experiment

The insurance product was successfully marketed to 4,667 households between October 2010 and January 2011. Figure 2 provides a timeline for project activities. The precise dates varied across the three states (owing to variation in the monsoon calendar), but in every state, a baseline survey was conducted before insurance marketing. We recorded rainfall (to determine payout eligibility) just before and during the planting period for the main (*Kharif*) season. If the village qualified, then the payout would occur about two months after planting (but before the harvest). We conducted a follow-up survey in each state about 1-2 months after the *Kharif* harvest.

We designed a "Delayed Monsoon Onset" index-based insurance product under-written and marketed by the Agricultural Insurance Company of India (AICI). AICI first defined an expected onset date of the monsoon using historic rainfall data. Monsoon onset is defined as a certain level of rainfall accumulation (varied between 30-40mm). The monsoon is considered delayed if the target amount of rainfall is not reached by one of three pre-selected "trigger" or payout dates.[14] The three trigger dates varied across villages. In many villages, the first (Rs.300) payout came if the monsoon was 15 days late; a larger (Rs.750) payout came if the monsoon was 20 days late; and the largest (Rs. 1200) came if the monsoon was 25 days late. In other villages, the same triggers were associated with delays of 20, 30, or 40 days, rather than {15, 20, 25}. The insurance company sought to keep the payout amounts {300, 750, 1200} and probabilities constant across villages for administrative ease, and they therefore varied the definition of rainfall delay associated with those payouts based on actuarial calculations. The price for a unit of insurance set by AICI also varied across villages from

[14] The product was designed this way so that it is simple and easily comprehensible to rural farmers in India, and meant to indemnify agricultural losses due to delayed rainfall.

Rs 80 to Rs 200 (USD 1.6 - 4), with an average price of Rs 145. This is an index product where all farmers in the village would receive the same payout per unit of insurance purchased.

Insurance offers were further subsidized in our experiment to ensure adequate take-up, thereby enabling a study of the effects of insurance. In this paper, we report only intent-to-treat pure experimental estimates based on insurance offers, and do not use variation stemming from actual take-up. We had randomly varied the extent of the subsidy. The experiment offered 0%, 10%, 50% or 75% discounts on this price, and Figure 3 shows that most of the insurance was purchased at highly subsidized rates. The overall take-up rate was 42%, and the rate was similar across cultivators and agricultural laborers. 98% of these households had no prior exposure to formal insurance. A downside of the heavy subsidization is that the insurance effect on labor supply for those who paid for insurance but were in villages with no payouts will be attenuated because this mechanism operates through a wealth effect, which is no longer substantial under subsidies. In contrast, the insurance payouts (up to Rs. 1200 per unit), though applicable to a small fraction of households, were substantial.

3.3 Variables of Interest: Insurance Offers, Rainfall and Payouts

We first test the labor demand and supply implications of the model using the randomized individual-level variation in insurance offers, which are expected to affect labor supply decisions for wage workers, and risk-taking and labor demand by cultivators. We compare, for example, the labor demand of cultivators randomly selected to receive an insurance offer against cultivators randomly chosen to not receive the insurance offer. The model also predicts that labor supply decisions of the insured will be affected by the occurrence of an insurance payout. The payout is induced by exogenous variation in the realization of rainfall in 2011, and four villages in Andhra Pradesh (AP) qualified for a payout.

Summary statistics from our analysis samples in Table 2 shows that 14-15% of sample households lived in villages that received payouts. That payout was the largest potential amount (Rs. 1200 per unit of insurance purchased) in one village, Rs. 750 per unit in another village, and Rs. 300 per unit in two villages. Figure 4 shows the variation in total rainfall during the *Kharif* season across all sample villages in AP. While payouts are strongly negatively correlated with total rainfall, the figure also indicates that the correlation is not perfect. The onset of monsoon was not delayed in some villages that ultimately experienced low rainfall. Our regressions will therefore control for a measure of the rainfall shock experienced in 2011 while studying the effects of the insurance payout.

The model predicts that the insured would supply relatively less labor when insurance payouts occur compared to workers with no insurance in the same rainfall state. We therefore compare individual labor supply choices of the insured and uninsured *within* payout villages and control for differences across villages by village fixed effects. For our general-equilibrium wage estimates, however, we look at the effects of insurance payouts *across* villages. For that analysis it is important to know whether payout and non-payout villages differ systematically in terms of their long-run rainfall conditions,[15] or whether the payout in 2011 can be treated as an exogenous shock.

We use rainfall data collected by the REDS survey in all our sample villages for the period 1999-2006 to compute the historical mean rainfall during the *Kharif* season in each village, and the inter-annual coefficient of variation of that rainfall. Table 3 reports these moments of the rainfall distribution and a *t*-test of differences across the payout and non-payout villages. We see that over the period 1999-2006, the rainfall distribution is statistically identical across the two sets of villages. The mean and coefficient of variation varies by only 1-2%, and are statistically indistinguishable.

[15] In principle, this should not be a concern, because AICI tailored the insurance contract design details for each village on the basis of that's village's historical rainfall distribution (e.g. the trigger dates and length of trigger periods varied across villages, and the monsoon onset date was village-specific). Some villages therefore did not have a higher ex-ante probability of payouts than others, because AICI adjusted trigger dates and unit prices to keep payout probabilities constant.

The table further shows that the payouts occurred because *Kharif* 2011 happened to be an unusually bad rainfall year in the payout villages, but it was a relatively good year in the non-payout villages. The payout villages had 2 mm/day deficiency in rainfall during *Kharif* 2011 relative to their historical average. In contrast, the villages that did not qualify for the payout experienced 4 mm/day excess rainfall relative to their historical average. Payout villages thus evidently experienced a random negative rainfall shock in 2011, although their long-run rainfall distribution is statistically identical to villages that did not qualify for a payout. This indicates that payout villages are not more susceptible to shocks *in general*.

3.4. Follow-up Sample

We collected follow-up data after the *Kharif* harvest in each of the three states (see Figure 2). The follow-up sample comprised of all households we marketed insurance to plus an additional 1619 control households living in the 46 villages, selected using same sampling frame (i.e. cultivators and agricultural laborers as reported in the REDS survey, and belonging to the same 118 large castes). The survey collected detailed information from cultivators on their input choices, labor use, and other farming decisions separately for every step of the agricultural cycle – land preparation, planting, weeding, harvest, etc. For landed cultivators, this allows us to estimate the determinants of their labor demand specifically during the harvest stage (which are expected to be affected by insurance and the realization of rainfall during *Kharif* 2011), and construct placebo tests using data on labor use during the planting stage (which should not have been influenced by the weather shocks or payouts). For landless wage worker households, our survey elicited information on the total number of days of agricultural labor supplied during *Kharif* 2011, total earnings and the wage rates received for each adult. Agricultural wages in rural India vary by gender and age (and possibly education), and we collected information on these demographic factors from all respondents.

Table 2 provides summary statistics on the variables used for analysis in three samples: (1) Cultivators who own more than one or two acres of land (and therefore likely to hire labor), for our labor demand estimation; (2) Landless agricultural wage workers aged 25-49 (who supply most labor) for the labor supply estimation; and (3) All landless workers who report daily wages, used for the estimation of the determinants of wage rate. An important statistic in the table is that only 2.3% of wage workers out-migrated during the *Kharif* season, and we will therefore focus on labor supply within the village in our estimates, and treat the village as the relevant labor market.[16]

4. Empirical Results

4.1 Effects of Rainfall Insurance on Cultivators: Risk-Taking and Labor demand

The key implication of the model for labor demand is that insured cultivators will choose riskier technologies compared with uninsured cultivators. As a result the output of the insured will be higher in good rainfall states but lower in bad rainfall states compared with that of the uninsured, and we should thus observe that the elasticity of labor demand with respect to rainfall should be larger for insured cultivators. To test this hypothesis we estimate the following labor demand specification for cultivator *j* in village *k*:

$$L_{jk}^{D} = \beta_1 I_{jk} + \beta_2 (I_{jk} \cdot R_k) + \beta_3 OwnedArea + \boldsymbol{K}_k + \varepsilon_{jk}^{1},$$

where L^{D}_{jk} is the total number of harvest-stage labor days employed by the farmer. We asked all landowning cultivators details on the cost of cultivation, including the number of days of labor used for each stage of production (land preparation, transplanting, weeding, harvesting etc), separately for permanent, casual, and family labor. Our main dependent variable is casual labor hired in for

[16] Migration after the conclusion of the *Kharif* season is of course possible as an *ex-post* labor supply response to rainfall or wage shocks. Our follow-up survey was conducted soon after the *Kharif* harvest to collect accurate agricultural data, and we do not have information on migration during the lean season. We will use the presence of bus stops and paved roads in the village (the same variables that Jayachandran 2006 used) to proxy for the ease of migration in the wage equation. The labor supply and demand equations will include village fixed-effects to control for all time-invariant village characteristics including ease of migration and access to credit institutions.

harvest tasks, aggregated across adult male and female labor. I_{jk} is an indicator variable for whether or not the cultivating household was offered insurance at the beginning of the *Kharif* season; R_k is the 2011 village-specific rainfall shock, measured as the rainfall deviation during *Kharif* 2011 from historical mean rainfall (during 1999-2006) collected from REDS; $\boldsymbol{K}_k$ is a vector of village dummy variables; and ε_{jk}^{1} is the error term. The set of village indicators absorb all differences across the villages, including realized and historic rainfall, as well as input prices. We also include caste fixed effects in the specification, in order to absorb variation in insurance treatment stemming from randomization by caste, as well as differences across castes that affect insurance take up (Mobarak and Rosenzweig, 2014). Standard errors are clustered by caste-village groupings in all regressions.

β_1 is the intent-to-treat (ITT) effect of insurance (offers) on harvest labor demand when rainfall is at its village-specific average level (the rainfall deviation is zero). β_2 is an estimate of how labor demand varies with rainfall across the "insured" (offered insurance) and "uninsured" (not offered insurance) farmers in the same village. Following the theory, we expect that $\beta_2>0$ – labor demand will be more sensitive to rainfall for insured cultivators relative to uninsured cultivators. The difference in the demand for harvest labor between the treated and the untreated, $\beta_1 + \beta_2 R_k$, thus depends on the weather shock realization R_k. This specification therefore permits the treatment effect on labor demand to change sign as the rainfall shock turns from negative to positive, consistent with our technology specification and with direct evidence on the insurance effects of crop choice.

To estimate the harvest labor demand equation, we use the sample of respondents who report making cultivation decisions and who own at least 2 acres of land, to ensure that we do not inadvertently include any cultivators who are net suppliers of labor. This subset of farmers is in the top 25% of the distribution of land ownership among landowning cultivators.[17] The first column of Table 4 shows that, consistent with the theory, the estimate of β_2 is positive and statistically significant: the demand for harvest labor is significantly more sensitive to realized rainfall for cultivators offered insurance relative to comparable farmers not offered insurance in the same village. The point estimate indicates that for every extra mm per day of rainfall, given historic mean rainfall, insured cultivators utilize two more days of harvest labor than do the uninsured, an 8% increase in relative demand.

The β_1 coefficient indicates that when rainfall is normal (at its long-run village average), insured cultivators hire two more days of labor than the uninsured, but this effect is statistically insignificant. The β_1 and β_2 point estimates together indicate that in the best rainfall state (i.e. the highest sample value of R_k in 2011), insured cultivators hire 25-30 days more harvest labor than uninsured cultivators. More interestingly for drawing welfare conclusions about the landless, and consistent with the evidence on output sensitivity to rainfall in Figure 1, the estimates imply that during drought conditions (using the R_k in the village that experienced the worst rainfall shock in 2011), insured cultivators use 5-9 days *less* harvest labor than do the uninsured, although the effect is only statistically significant at the 10% level (one-tail test). There is thus evidence that insuring cultivators makes the landless worse off in some adverse states of nature.

Figure 5 plots the estimated insurance treatment effect on labor demand across the entire rainfall distribution experienced in 2011 in our sample villages. Labor demand by insured cultivators is statistically significantly higher (relative to the uninsured) for almost all positive rainfall shocks experienced in 2011. Labor demand by insured cultivators is also lower for all sample negative rainfall shocks, but the estimates in this range are only marginally statistically significant.

[17] We show below that our results are robust to changes in this acreage cutoff.

We assumed in the model that farmers profit-maximize in the harvest period; i.e. that once planting-stage decisions are made cultivators do not face liquidity constraints on harvest-stage inputs. To test this we exploit the fact that in some of the villages insured farmers received non-trivial insurance payouts after the rainfall was realized, thus substantially after the planting stage concluded but during the harvest season.[18] Harvest labor demand should be no different across insured and uninsured farmers in payout villages, if there are no liquidity constraints. The second column of Table 5 adds a separate indicator for farmers receiving insurance offers in villages that qualified for a payout. Receiving a potentially substantial payout only led to a statistically insignificant 2 extra days of labor hired during the entire harvest period. We cannot reject the hypothesis that the payouts had no effect on labor demand and the insurance rainfall sensitivity coefficient remains statistically significant in this specification.

To assess if these results on the increased rainfall sensitivity of harvest labor demand for insured cultivators are spurious, we also carried out a placebo test. According to the model, the sensitivity of planting-stage labor to rainfall that is realized over the course of the *Kharif* season should not be affected by whether or not cultivators are offered insurance, as planting-stage preparations are made prior to the bulk of rainfall realizations. To test this we employed the same labor demand specification but replaced total harvest labor days by planting-stage (land-preparation) labor days. This category of labor demand includes labor used for sowing and soil preparation. Column three shows that in contrast to the estimates for harvest labor, the effect of realized rainfall on the difference in demand for planting-stage labor across insured and uninsured cultivators is not statistically different from zero. Moreover, the estimates indicate that cultivators offered insurance evidently did not employ more planting-stage labor. In the last column of the table we also report

[18] The payouts were made in the late fall of the *Kharif* season.

estimates including the insurance offers in payout village interaction, and this too is not statistically significantly different from zero, which is expected given the timing of the payouts.

4.2. Rainfall Insurance, Payouts and Labor Supply

To test Proposition 1 of the model, we estimate the determinants of agricultural labor supply – total days worked and participation – during the *Kharif* season for members of landless agricultural labor households aged 25-49. Theory predicts (see Table 1) that harvest-stage (i.e. post-rainfall and insurance payout realizations) labor supply will differ between the insured and uninsured wage laborers depending on whether insurance payouts occur. We therefore estimate labor supply equations separately for payout and non-payout villages, and focus on the effect of insurance offers on the propensity to supply harvest labor within each type of village. As indicated in Table 1, comparing labor supply responses between payout and non-payout villages is not informative because the equilibrium wage rates will be different (due to different rainfall realizations).

There are two limitations of our data and experimental design that are pertinent for implementing the tests of labor supply effects from insurance provision. First, unlike for labor demand, which is measured by stage of production, labor supply is measured over the full *Kharif* season. The labor supply measure thus includes agricultural work undertaken prior to the full realization of the rainfall shock and prior to the payouts. 40% of those who were offered insurance in payout villages purchased and received substantial payouts. Such workers thus had significantly higher non-earnings incomes than the uninsured during the peak harvest stage of production. However, because pre-payout labor is included in the labor supply measure, the wealth effects associated with payouts that are the source of the difference between the labor supply of the insured and uninsured are attenuated.

The second limitation is that the wealth effect for the insured who received no payouts is relatively small due to the heavy subsidization of insurance contracts offered. While all the insured paid some premiums, Figure 3 shows that the vast majority who purchased insurance bought the contract at highly subsidized rates (randomized discounts of 75% or 50%). The net costs of subsidized insurance (Rs. 80 per unit) are far below the values of the indemnification payouts (Rs. 510 on average) in the payout villages. The model predicts positive labor supply effects from insurance in non-payout villages if there is an adverse wealth effect from paying the premium, but in reality there was not much of a wealth effect. Indeed, the expected wealth of workers purchasing subsidized insurance increased. Given that labor supply is measured over the full *Kharif* season, labor supply reflects choices made when all insured workers were feeling flush. The upshot is we have a strong test for labor supply effects in the payout villages – the labor supply of the insured should not be higher than that of the uninsured - and a weak test for labor supply effects in the non-payout villages - given the subsidies, the insured in those villages could even work less than the uninsured overall.

The labor supply specification allows the effect of insurance to vary by rainfall, in order to be symmetric with the labor demand specification. For each village type the equation we estimate is

$$L_{ijk}^{S} = \alpha_1 I_{jk} + \alpha_2 (I_{jk} \cdot R_k) + \boldsymbol{Z}_{ijk}\pi + K_k + \varepsilon_{ijk}^{2}$$

I_{jk} is again the indicator for randomized insurance offers, and R_k is again the 2011 village-specific rainfall shock relative to historical mean rainfall. $\boldsymbol{Z}_{ijk}$ is a vector of person-specific characteristics (age, age squared and gender), and ε_{ijk}^{2} is the error term. Standard errors are again clustered by the unit of randomization (caste-village groupings). We control for both village fixed effects and caste fixed effects, which means that all contrasts between the insured and the uninsured are within village and caste. The village dummy variables absorb all differences across villages in realized and historic rainfall and other determinants of labor supply at the village level.

For the first two columns of Table 5, L^S_{ijk} is defined as an indicator of whether or not a worker *i* in landless household *j* [19] in village *k* participated in the agricultural labor market during *Kharif* 2011. The two columns estimate this equation separately for workers in payout and non-payout villages. The dependent variable for the last two columns is the number of days of actual wage employment in the local agricultural labor market during the season among members of landless households who worked in that market.

Our model (Proposition 1) predicts that the insured will supply less labor than the uninsured in villages that qualify for a payout, due to the income effect of the payout (1a). Proposition 1a therefore predicts $\alpha_1<0$ and $\alpha_2<0$ in payout villages, i.e. that the insured work less, and their labor supply is less sensitive to realized rainfall. We estimate exactly this in column 1 of Table 5. Insured laborers are 11.7 percentage points less likely to work than the uninsured in the villages that qualified for a payout at the median rainfall shock in the payout villages (1.9mm below the historical mean).

As noted, there was no large wealth effect from purchasing subsidized insurance in the villages that did not receive payouts. The second column in Table 5 shows that there is no statistically significant difference in the agricultural labor-force participation rates of the insured and uninsured at median rainfall in those villages (5.0 mm per day above the historical mean).

In the third and fourth columns of Table 5 we report the estimates of the effects of insurance in payout and non-payout villages, respectively, on days worked in the agricultural labor market during the *Kharif* season. The results are similar for the intensive margin of labor supply. In the payout villages, $\alpha_1<0$, which implies that the insured who received payouts work fewer days than the uninsured under normal rainfall conditions. The estimated magnitudes of α_1 and α_2 are such that the insured who receive payouts work less than the uninsured under almost the entire observed rainfall distribution. At the median level of rainfall shock in payout villages, those offered insurance

[19] Pure agricultural labor households were defined by the primary occupation of the head of the household in 2006.

worked approximately 20 fewer days during the *Kharif* season compared with uninsured workers. Paralleling the participation results, the insured in the non-payout villages supplied no less labor than the uninsured (point estimate of 0.1 days, not statistically significant).

Is the estimated 20-day reduction in labor supply reasonable, given the magnitude of the wealth effect associated with insurance payouts? Our wage estimates indicate that harvest wages in the village fall sharply to about Rs. 60 per day during the type of drought experienced in villages that qualified for payouts. The insured therefore ceded an extra Rs. 1200 of agricultural labor income in payout villages. The average payout was Rs. 510 per unit, and the insured purchased 2 units of insurance on average. The expected payout was therefore Rs. 1020. The income loss associated with the reduction in labor supply appears comparable to the value of the insurance payout.

5. General Equilibrium Wage Estimation

The labor-market equilibrium model indicates that wage volatility across rainfall states depends on the fractions of cultivators and wage workers who are insured. In particular, the model predicts that insuring more cultivators increases the sensitivity of wages to rainfall through the labor demand channel (Proposition 3). We have already observed the underlying mechanism in the labor demand equation we estimated – the harvest labor hired by a cultivator becomes more rainfall sensitive if he is offered insurance. Symmetrically, the model also implies that wages become less volatile across rainfall states when landless laborers are insured (Proposition 2). Table 5 demonstrates the underlying mechanism: insured wage workers supply less labor when they receive payouts. Testing the aggregate wage effects of these mechanisms requires variation in the proportions of cultivators or agricultural laborers in the village with insurance offers. We first describe how our experimental design yields such variation, and explore whether this variation can be treated as random before presenting the general-equilibrium wage estimates.

5.1 Variation in Fractions of Cultivators and Laborers Insured

About 26% of all cultivators and 32% of all laborers received insurance marketing in the average village, but these fractions vary between 0% to 53% for cultivators, and between 0% to 100% for laborers. The variation in the proportions of farming households in a village that are insured comes from the two-step randomization process, where certain castes were first randomly chosen for insurance offers before random subsets of those caste members were offered contracts. To illustrate, if one of the 93 castes randomly chosen for insurance is relatively populous in village A but sparse in village B, whereas the dominant caste in village B is randomly assigned to be a 'control caste' not receiving insurance, then the fractions of cultivators and agricultural laborers receiving insurance offers would be greater in village A. The two-step randomization procedure therefore generates the required variation in fractions of laborers and cultivators insured, simply because castes are not evenly distributed across villages, and only some castes were randomly chosen to receive insurance offers.

The identification of general-equilibrium wage effects from insuring cultivators and the landless relies on the assumption that the cross-village variation in the fraction of cultivators and landless who are offered insurance is random. A key concern is that our sampling procedure eliminated all "small castes" (with fewer than 50 members in the REDS listing survey) from our sample frame.[20] This reduces the numerator (number of insurance offers to cultivators and to laborers) in each of our two variables of interest. The 50-member rule eliminates 19% of the population from insurance marketing, and this fraction varies between 0% and 86% across villages because the size distribution of castes varies across sample villages. This variation potentially creates some correlation between our variables of interest (fractions of cultivators and laborers insured) and other factors such as the number of castes in the village or the concentration of caste membership, because the fraction of farming households *in large castes* (i.e. satisfying the 50-member rule) may be correlated with such variables. This implies that our variables of interest can be treated as random only *conditional on* the fraction of the village population in large castes. Because we specified the sampling rule based on observable variables, we can control for it directly.

A closely-related concern, because we are separately studying the effects of cultivators and laborers receiving offers, is that the cultivator-laborer balance in the population may vary across locations. If, for example, cultivators are heavily concentrated in large castes in certain villages, then that might introduce some non-random variation in our variables of interest. Our wage equations will therefore control for the fraction of cultivators in the village who are members of large castes separately from the fraction of landless laborers in large castes. Furthermore, we will condition on

[20] The original experimental design focused on the effects on formal insurance take-up of variation across castes in the ability to risk-share (Mobarak and Rosenzweig 2014). We sampled large castes in order to estimate those more precisely. Selection by caste does not affect our labor demand and supply estimates, which were obtained using caste fixed-effects.

the population shares of cultivators and laborers in the village, and rely only on variation in the subsets of those cultivators and laborers who were randomly assigned to receive insurance offers.

Table 6 examines the quantitative relevance of these concerns, and shows how these conditioning variables eliminate any correlation (that might have been introduced by the sampling strategy) between the fractions of cultivators and laborers randomly selected for insurance offers (which are our variables in interest), and caste and village characteristics likely related to the sampling rule. Column 1 reports the correlations between the fraction of the population satisfying the sampling rule, and village size, number of castes, and measures of caste diversity. In column 2 we examine how these same village and caste characteristics are correlated with our variables of interest – fractions of cultivators and laborers who receive insurance marketing. As expected, we see some significant correlations in both columns, so these variables cannot be treated as random in an unconditional sense.

Columns 3 and 4 report the correlations that are most relevant for our wage equation estimation, which are correlations between our variables of interest and village and caste characteristics *conditional on* the sampling variables we will be controlling for in our wage regression. In column 3, we control for the fraction of cultivators or laborers satisfying the sampling rule, and all the correlations become smaller and statistically insignificant.[21] In column 4 we condition on state dummies, fractions satisfying the sampling rule, *and* population shares of cultivators and laborers. All eight correlations remain statistically insignificant. The only coefficient that appears sizable is on "number of castes." We will therefore later conduct sensitivity tests of our wage estimates controlling for this variable.

Our identification assumption for the wage estimation therefore is that the proportions of cultivators and laborers receiving insurance offers are exogenous, *conditional* on the population shares

[21] We regress the fraction of cultivators in the village receiving insurance offers on the fraction of cultivating households in the village, generate residuals, and correlate those residuals with the village and caste characteristics.

of cultivators and laborers, and the fractions of cultivators and laborers in large castes (i.e., our sampling rule).

5.2 Estimating Equation for General-Equilibrium Wage Analysis

We estimate the equilibrium wage equation for a sample of agricultural wage workers age 20 and above including both individual-specific and village-specific variables:

$$\ln(W_{ik}) = \gamma_1 CI_k + \gamma_2 CI_k \cdot r_k + \gamma_3 LI_k + \gamma_4 LI_k \cdot r_k + \gamma_5 IP_k + \boldsymbol{Z}_{ik}\boldsymbol{\alpha} + \boldsymbol{V}_k \Delta + \varepsilon_{ik}^3$$

W_{ik} is the *Kharif* 2011-season log of the daily wage rate directly reported in our survey by a landless laborer i in village k. CI_k is the fraction of cultivators in the village who received randomized insurance offers; LI_k is the fraction of landless laborers who received randomized insurance offers; IP_k is the fraction of households offered insurance in payout villages; r_k is the village-specific amount of rain during the *Kharif* 2011 season; $\boldsymbol{Z}_{ik}$ is a vector of person-specific determinants of wages, including gender, age, age-squared and indicators for primary and secondary school attainment; and $\boldsymbol{V}_k$ is a vector of village-level characteristics. This vector includes the sampling variables (proportion of cultivators and laborers in large castes), the proportion of cultivators and laborers in the population, village rainfall during *Kharif* 2011 (r_k), its squared term, and the historic average rainfall in the village for the period 1999-2006, so that variation in r_k identifies the effect of the 2011 rainfall shock.[22] Further, we control for eleven different soil type variables including soil color (red, gray, black), type (soft or hard clay), percolation speed, and soil depth and drainage characteristics.

The RHS village-level variables of interest that provide a test of the general-equilibrium predictions of the model are:

[22] Unlike the labor demand and supply equations, we include the level of rainfall in 2011 and historical rainfall average separately because we cannot control for village fixed effects (we have only one season of wages). Wages are thus affected by rainfall levels, and it is important to capture this level effect for the policy simulations we conduct later.

a) The interaction between CI_k and rainfall during the *Kharif* 2011 season, r_k. A positive coefficient (γ_2) on this interaction would imply that insuring cultivators increases wage volatility across rainfall states (Proposition 3).

b) The interaction between LI_k and r_k. A negative coefficient (γ_4) on this interaction would imply that insuring wage workers decreases wage volatility across rainfall states (Proposition 2).

c) IP_k . This coefficient (γ_5) reflects the general-equilibrium wage effect of insurance payouts, and should be positive if, as we found, landless laborers supply less labor when insurance payouts occurs.[23]

d) $CI_{k.}$ This coefficient (γ_1) is the effect of insuring cultivators on the (log) equilibrium wage at zero rainfall. Our findings on insured cultivators' risk-taking (Figure 4) and labor demand (Table 4) suggests that this could be negative. If it is, then it raises the possibility that insuring cultivators lowers the equilibrium wage in low-rainfall states. The total wage effect of insuring cultivators is $\gamma_1 CI_k + \gamma_2 CI_k\, r_k$.

Finally, while our model focuses on the roles of risk and insurance in wage determination, Jayachandran (2006) has shown that missing credit markets and transportation frictions can contribute to wage volatility. We collected data on all the variables that proxy for market imperfections in her paper: the presence of a bank, a bus stop, and a paved road in the village, and control for their direct effects, and their interactions with rainfall (r_k).[24] With these controls, we can verify that our insurance variables do not merely pick up the effects of other market failures such as lack of credit or lack of migration opportunities, and we can test an implicit assumption of our one-period model, that agents cannot perfectly smooth consumption across periods. As Jayachandran

[23] Recall that insurance payouts had no effect on labor demand (Table 4).

[24] Her analysis also included village proximity to a railway. None of our sample villages were within 100 km of a railway station.

has shown, wages will be less sensitive to rainfall realizations, via labor supply general-equilibrium effects, when there is greater access to credit and or migration opportunities in the off-season.

5.4. Estimation Results on General Equilibrium Wages, and Policy Simulations

The estimates of the general-equilibrium wage equation are shown in Table 7. The errors ε_{ik}^{3}, are clustered by the unit of randomization of insurance offers, which is the caste-village grouping. The first column of Table 7 omits our insurance variables of interest to replicate the general-equilibrium wage specification in Jayachandran (2006). This helps establish that the wage-setting in our sample of villages is not unusual, and tests for households' inability to smooth consumption across periods. Our estimates conform to her main findings, which used district-level data from across all of India. The presence of banks, paved roads, and bus stops (all of which offer better income smoothing opportunities via credit or migration) reduces the sensitivity of wages to rainfall variation. Thus, households cannot perfectly smooth consumption across periods.[25]

We add our insurance variables in the second column of Table 7. The set of coefficient signs is consistent with the model. First, we find evidence consistent with Proposition 3: $\gamma_2>0$, which implies that offering insurance to a larger proportion of cultivators in the village increases the sensitivity of wages to rainfall. This result mirrors the labor demand estimates displayed in Table 5 – when rainfall is ample, insured cultivators hire more harvest labor than uninsured cultivators. Furthermore, $\gamma_1<0$ and is highly significant, which implies that during droughts, wages actually fall even further in villages where more cultivators are insured. These two results are consistent with cultivators taking more risk when insurance is offered. The wage results are also consistent with the labor demand estimates from Table 4 and Figure 5, which show that insured cultivators hire significantly more labor during good rainfall states, but less labor than the uninsured during

[25] As seen in Table 2, while migration during the *Kharif* season is rare in our sample, the infrastructure variables allow us to control for village-level differences in the opportunities to smooth consumption by migrating in the off-season.

droughts. Insured cultivators take more risk (Figure 4), and evidently have bumper harvests under good rainfall conditions which lead to greater labor demand, but they suffer larger losses during droughts, and cut back on hiring labor under such conditions even more than the uninsured.

These estimates suggest that there are adverse spillover effects on landless laborers from selling insurance to cultivators. Wages become more volatile, and the landless are worse off in some states of nature, especially if they are uninsured. The point estimates indicate that a 10% increase in the fraction of cultivators who are insured leads to a 33% lower wage rate at the 20th percentile of rainfall, but a 29% higher wage rate at the 80th percentile of rainfall. Insurance for cultivators leads to substantially greater wage volatility.

Second, we find evidence consistent with Proposition 2: $\gamma_4<0$ - offering insurance to a larger proportion of laborers in the village decreases the sensitivity of equilibrium wages to rainfall. Our labor supply estimates show that this is likely because of the labor supply responses to insurance in villages that qualified for a payout. We also find a direct general-equilibrium effect consistent with that mechanism - our estimate of γ_5 is positive and statistically significant, which indicates that wages rise when a larger fraction of people are offered insurance in the payout villages. This effect is also substantial; a 10% increase in insurance marketing would increase the equilibrium wage rate by 24.7% in villages that qualify for insurance payouts.

The set of general- equilibrium wage rate estimates allow us to conduct simulations to predict the equilibrium wage profiles under alternative policy scenarios where cultivators or wage workers are offered insurance in isolation, or in combination. Evaluating the rainfall sensitivity of wages under these scenarios is realistic and policy-relevant because most of the rural, agrarian developing world is not yet covered by formal weather insurance, and even when insurance is introduced, it is typically designed for and marketed only to cultivators.

Figure 6 plots the predicted wage-rainfall relationship based on the general-equilibrium wage estimates in column 2 of Table 7 under two policy scenarios: (a) there is no insurance in the village, and (b) insurance is marketed to 25.6% of cultivators, which is the fraction receiving insurance marketing across our sample villages. For this simulation we assume that landless laborers do not receive insurance, reflecting real-world insurance marketing conditions. We otherwise assume an "average" village in our sample in terms of access to banks, paved roads, bus stops and proportions of cultivators and wage laborers in the village population. We plot predicted log wages for the 20th percentile to the 80th percentile of rainfall observed in our sample villages.

Figure 6 shows that the sensitivity of wages to rainfall increases when cultivators are offered insurance. The effect of moving from no coverage to having 26% of cultivators covered by insurance on wages is quite dramatic in periods of low rainfall. At the 30th percentile of rainfall, wages are 25 rupees per day (42%) lower. As a benchmark, the average daily wage reported by laborers in our sample is 120 rupees. At the median level of rainfall experience in our sample in 2011, wages decrease by 21%, or 17 rupees per day. The effect turns positive at the 52nd percentile of rainfall, and at the 70th percentile of rainfall village wages are 34 rupees per day (30%) higher. These results indicate that wages become much more volatile when cultivators are offered insurance, and the shapes and positions of the two curves in Figure 3 indicate that the greater volatility dominates any effect on average wage levels.

Next we simulate the wage effects of providing insurance for landless agricultural laborers. Figure 7 plots predicted wages across rainfall states under two policy scenarios: (a) no insurance for landless laborers, and (b) insurance marketed to 31.8% of laborers, which is the fraction receiving insurance marketing in our sample villages. We again simulate these effects for an "average" sample village in terms of infrastructure and cultivator/labor balance. We now hold the cultivator insurance marketing rate constant at 25.6% (our sample average) to approximate real-world conditions, as it is not realistic to market agricultural insurance to *only* the landless, leaving cultivators uninsured. We simulate effects for a village that qualified for an insurance payout, because our labor supply estimates indicate that this is the only interesting case: we only observe general-equilibrium and labor supply responses by insured workers in the payout villages.

Figure 7 shows that marketing insurance to landless laborers reduces the sensitivity of wages to rainfall. The general-equilibrium labor supply responses are such that wages rise during unfavorable rainfall states, which serves to indirectly insure the other landless in the village who did not receive insurance marketing. The magnitudes are quite substantial: wages rise by 26 rupees per day (42%) at median rainfall, and by 30 rupees per day (91%) at the 30th percentile of rainfall when insurance is marketed to laborers. This wage effect stays positive for the bottom two-thirds of the distribution of rainfall experienced by our sample villages in 2011.

In Figure 8 we combine the two policy simulations, and examine the effects of marketing insurance to both cultivators and landless laborers simultaneously. The opposing rainfall sensitivity effects from cultivator choices and laborer choices evidently cancel each other out, and wages are no more volatile when both cultivators and laborers are offered insurance, relative to the case of no insurance in the village. Overall, there is a slight increase in average wages with insurance compared to a regime of no insurance, which is consistent with the prediction from the theoretical model (where greater investment in the input x by insured cultivators leads to higher wages). Wages increase by 10% (5 rupees per day) at the 30th percentile of rainfall, by 12% (10 rupees per day) at median rainfall, and by 17% (20 rupees per day) at the 70th percentile of the rainfall distribution as a result of providing rainfall insurance to both cultivators and laborers.

6. Robustness Checks and Additional Empirical Implications

In this section we explore the sensitivity of the labor demand and wage results to two key assumptions we made in the estimation section. First, Table 8 repeats the first two (harvest labor demand) specifications from Table 4, but alters the acreage-based definitions of pure cultivators. Our results are robust to using a 0.5 acre, or 1 acre or 3 acre cutoff, or virtually any sensible cutoff. Only 10% of landowning cultivators in our sample own more than 3 acres of land. The table shows that the results get larger and stronger when larger cutoffs are used (which eliminates more and more of the cultivating households who may also be supplying some labor). In every case, (a) insurance makes cultivators' harvest labor demand more sensitive to rainfall (i.e. $\beta_2 > 0$), (b) insured cultivators hire less labor than the uninsured during droughts, and significantly more during good rainfall states, and (c) under "normal" or "expected" rainfall conditions, the insured hire slightly more harvest labor (i.e. $\beta_1 > 0$).

Table 9 re-estimates the general-equilibrium wage equation, but directly controlling for the village and caste characteristics that are conceptually correlated with our variables of interest (proportions of cultivators and laborers in the village receiving insurance offers), given our caste-based sampling rule. Table 6 showed that the number of castes in the village and the size of the largest caste had some residual correlation with our variables of interest (of -0.15 to -0.2, even though not statistically significant), and in this specification, we add these as controls to the wage equation. All of the main wage results remain unaffected: (a) wages are more rainfall-sensitive when a larger fraction of cultivators in the village receive insurance offers, (b) wages are less rainfall-sensitive when more laborers are insured, and (c) wages are higher in payout villages.

Finally, an implication of the model is that rational and informed landless labors will anticipate greater wage volatility when there is greater insurance coverage among cultivators. During our experiment, the marketing of insurance was done one village at a time and was quite conspicuous. We see this cross effect in our data - we estimated an insurance demand specification for landless laborers, and find that laborers were more likely to purchase insurance when insurance was offered to a larger fraction of cultivators in the village, controlling for the fraction of non-cultivators offered insurance. We do not show this result because other social learning or imitation mechanisms, or simply differences in the capabilities of the insurance marketers across villages, could also explain this demand spillover, and we do not have the data to distinguish between these alternate mechanisms. We view this result as only further suggestive evidence in favor of the general-equilibrium labor market model.

7. Concluding Comments

Comparing the effects of combined insurance marketing (Figure 8) to the effects of marketing to the supply and demand sides in isolation (Figures 6 and 7) demonstrates the value of pairing general-equilibrium analysis based on a model of the relevant market, with data generated by a randomized controlled trial. The net effect of insurance marketing on the wage distribution (mean and volatility) is small in Figure 8, but this masks significant opposing effects on volatility from the demand and supply sides, exactly as predicted by the model. The analysis allows us to learn more about the economic environment, and enumerate a more complete range of costs and benefits of insurance marketing, relative to what a simple program evaluation would permit, even if that evaluation included regressions of spillover effects. Directly analyzing the labor demand and supply responses to insurance was also important, because this motivates and rationalizes the exact specification for the general-equilibrium wage estimation.

Designing randomized controlled trials of development and other social programs such that aggregate effects of interventions can be uncovered is an important next step for the research agenda on program evaluation. Providing sound policy advice requires us to estimate the effects of programs when they are scaled up by governments, accounting for the general-equilibrium changes that may occur as a result of the program at scale. This paper provides an example of how equilibrium effects can be estimated for an important economic and policy intervention: addressing a missing insurance market in an environment where the poor face large weather risk. The paper also illustrates the design challenge for RCT's: generating random variation both at the individual level and at the market level in sufficient magnitudes to affect aggregate prices.

Our research findings also yield a clear policy message – the current practice of designing insurance contracts on the basis of owned acreage, and marketing products only to landed cultivators likely reduces the welfare of the landless. These unintended spillovers create a more risky economic environment for those who have to rely exclusively on their own labor for their livelihoods. The problem is compounded because this same population is also denied the possibility of insurance coverage. Our general-equilibrium analysis highlights this adverse spillover effect on a non-treated population, but our experimental design and simulations also allows us to show that the problem can be addressed by expanding insurance coverage for this population.

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Table 1

Insured and Uninsured Landless Labor Supply in the *H* and *L* States		
State of nature	L	H
Insured labor supply	$1 - \gamma - \frac{\gamma(m + (1-p)I)}{w^L}$	$1 - \gamma - \frac{\gamma(m - pI)}{w^H}$
Uninsured labor supply	$1 - \gamma - \frac{\gamma(m)}{w^L}$	$1 - \gamma - \frac{\gamma(m)}{w^H}$
Difference insured and uninsured	$\frac{-\gamma(1-p)I}{w^L}$	$\frac{\gamma pI}{w^H}$

Table 2: Comparison of Rainfall Characteristics of Payout and Non-Payout Villages

	Non-payout mean	Payout mean	T-stat of difference*
Dev. of Kharif 2011 Rain per day from Historical Average	4.095	-2.066	-6.10
Rain per day during 2011 Kharif season	8.217	2.056	-7.28
Mean Historical Rainfall (1999-2006)	4.178	4.123	-0.11
Coefficient of Variation of Historical Rainfall	0.868	0.845	-0.16

*Standard Errors are clustered by village

Table 3: Sample Characteristics

	Mean	SD	N
Sample for Labor Demand Estimates	Cultivator Households, Acreage>=1		
Offered Insurance	0.603	0.489	1,293
Acreage Cultivated	2.98	4.49	1,292
Days of Harvest Labor	17.5	25.5	1,286
Days of Planting Labor	26.2	34.7	1,286
	Cultivator Households, Acreage>=2		
Offered Insurance	0.600	0.490	758
Acreage Cultivated	4.229	5.529	757
Days of Harvest Labor	24.797	30.801	754
Days of Planting Labor	37.238	41.129	754
Sample for Labor Supply Estimates	Landless Agricultural Wage Workers Aged 25 -49		
Offered Insurance	0.575	0.494	3,678
Age	35.5	6.99	3,678
Male	0.479	0.500	3,678
Deviation of Kharif 2011 Rain per Day from Historical Average	3.38	4.47	3,449
Village where Payout Occurred	0.140	0.347	3,678
Agricultural Labor Force Participation	0.345	0.475	3,676
Days of Agricultural Work conditional on Labor Force Participation	58.9	44.2	1,268
Migration during Kharif Season	0.023	0.151	4,272
Sample for General Equilibrium Wage Estimates	All Adult Landless Agricultural Wage Workers Aged 20+		
Offered Insurance	0.600	0.490	4,706
Age	43.3	14.0	3,872
Male	0.601	0.490	3,952
Bus Stop in Village	0.403	0.491	4,706
Paved Road to Village	0.896	0.305	4,706
Bank in Village	0.365	0.481	4,706
Rain per day during 2011 Kharif season	7.12	3.75	4,697
Historical Mean Rainfall	4.15	1.28	4,392
Village where Payout Occurred	0.150	0.358	4,706
Proportion Cultivators Offered Insurance in 2011	0.202	0.135	4,706
Proportion of Landless Labor Households Offered Insurance in 2011	0.252	0.160	4,706
Proportion of Agri. Labor Households in Castes Eligible to Receive Insurance	0.874	0.088	4,706
Proportion of Cultivator Households in Castes Eligible to Receive Insurance	0.849	0.182	4,706
Proportion of Village Households that are Cultivators	0.287	0.159	4,706
Proportion of Village Households that are Landless Agri. Laborers	0.382	0.176	4,706
Daily agricultural wage (rupees) in Kharif season	120	64.1	3,076

Table 4: Village Fixed Effects Estimates: Demand for Kharif Season Labor by Cultivators by Stage of Production
(Cultivators with at least 2 acres)

	(1)	(2)	(3)	(4)
VARIABLES	Days of Harvest Labor		Days of Planting Labor	
Offered Insurance in 2011	2.118	0.270	-3.160	-0.867
	(0.83)	(0.08)	(-1.19)	(-0.28)
Offered Insurance x Deviation of Kharif 2011 Rain per Day from Historical Average	1.995	2.651	0.575	-0.239
	(3.00)	(2.89)	(0.83)	(-0.27)
Offered Insurance in a Village where Payout Occurred		5.289		-6.564
		(0.86)		(-1.09)
Acreage Cultivated	2.053	2.055	2.358	2.356
	(2.02)	(2.01)	(2.05)	(2.05)
Observations	734	734	734	734
R-squared	0.398	0.398	0.355	0.355
Predicted Effect of Insurance Offer at Minimum Value of Rainfall Deviation (A Negative Rainfall Shock)	-5.009	-9.200		
	(-1.343)	(-1.496)		
Predicted Effect of Insurance Offer at Maximum Value of Rainfall Deviation (A Positive Rainfall Shock)	24.80	30.41		
	(3.267)	(3.519)		

Robust t-statistics, based on standard errors clustered by village-caste, in parentheses. All specifications control for village fixed effects and caste fixed effects.

Table 5: Village Fixed Effects Estimates: Labor Supply during Kharif Season by Landless Agricultural Wage Workers Aged 25 - 49

	(1)	(2)	(3)	(4)
Dependent Variable:	Agricultural Labor Force Participation: Any Agricultural Work?		Number of Days of Agricultural Work	
	Payout Villages	Non-Payout Villages	Payout Villages	Non-Payout Villages
Offered Insurance	-2.175	-0.194	-338.2	-1.582
	(-4.41)	(-4.08)	(-2.04)	(-0.46)
Offered Insurance x Deviation of Kharif 2011 Rain per Day from Historical Average	-1.084	0.0304	-167.3	0.295
	(-4.63)	-2.83	(-2.03)	-0.21
Male	0.195	0.114	6.745	8.334
	(-5.31)	(-4.02)	(-1.46)	(-3.59)
Observations	515	2,925	264	916
R-squared	0.211	0.33	0.2	0.223
Predicted Effect of Insurance Offer at the Median Rainfall Shock in Payout Villages	-0.117		-20.33	
	(-1.747)		(-1.226)	
Predicted Effect of Insurance Offer at the Median Rainfall Shock in Non-Payout Villages		-0.0421		-0.107
		(-1.264)		(-0.0147)

Robust t-statistics, based on standard errors clustered by village-caste, in parentheses. All specifications control for village fixed effects and caste fixed effects. Age and age-squared also included as controls.

Table 6: Correlations between Sampling Eligibility Variables and Village and Caste Characteristics

Agricultural Labors	Fraction of Agri. Laborers Satisfying the Sampling Rule (members of large castes who were eligible for insurance marketing)	**Fraction of agricultural labor households that received insurance marketing** (RHS Variable of interest in the wage estimation)	**Fraction of agricultural labor households that received insurance marketing** (RHS Variable of interest in the wage estimation)	
			Conditional on: Fraction of agri. laborers satisfying the sampling rule, state FEs	Conditional on: Fraction of agri. laborers satisfying the sampling rule, state FEs and population share of laborers
Total # of households in village	0.125	-0.103	-0.138	-0.134
	(0.794)	(0.658)	(0.882)	(0.854)
Total # of castes in a village	0.058	-0.385	-0.207	-0.208
	(0.367)	(2.638)	(1.340)	(1.342)
Proportion of village accounted for by largest caste	-0.145	0.056	0.047	0.056
	(0.924)	(0.355)	(0.295)	(0.355)
Measure of concentration of castes 1-sum(proportion^2)	0.152	-0.033	-0.021	-0.029
	(0.974)	(0.207)	(0.131)	(0.183)

Cultivators	Fraction of Cultivators Satisfying the Sampling Rule (members of large castes who were eligible for insurance marketing)	**Fraction of cultivator households that received insurance marketing** (RHS Variable of interest in the wage estimation)	**Fraction of cultivator households that received insurance marketing** (RHS Variable of interest in the wage estimation)	
			Conditional on: Fraction of cultivators satisfying the sampling rule, state FEs	Conditional on: Fraction of cultivators satisfying the sampling rule, state FEs and population share of cultivators
Total # of households in village	0.163	-0.079	-0.153	-0.132
	(1.042)	(0.503)	(0.978)	(0.841)
Total # of castes in a village	-0.29	-0.352	-0.096	-0.077
	(1.919)	(2.381)	(0.610)	(0.486)
Proportion of village accounted for by largest caste	0.256	0.047	-0.138	-0.152
	(1.674)	(0.298)	(0.879)	(0.975)
Measure of concentration of castes 1-sum(proportion^2)	-0.291	-0.073	0.123	0.137
	(1.927)	(0.465)	(0.786)	(0.878)

T-statistics in parentheses.

Table 7: General Equilibrium Effects of Insurance Provision and Rainfall on Log Wages
(Landless Agricultural Wage Workers Ages 20+)

	(1)	(2)
Proportion Cultivators Offered Insurance in 2011		-6.724
		(-3.12)
Proportion Cultivators Offered Insurance * Rain per Day in 2011 Kharif Season		0.842
		(3.96)
Proportion of Landless Labor Households Offered Insurance in 2011		4.357
		(1.76)
Proportion of Landless Labor Households Offered Insurance * Rain per Day in 2011 Kharif Season		-0.627
		(-3.10)
Proportion of Households Offered Insurance in a Village where Payout Occurred		2.470
		(2.66)
Rain per day during 2011 Kharif season	0.145	0.804
	(1.10)	(7.03)
Rain per day during 2011 Kharif season, squared	-0.00305	-0.0133
	(-1.38)	(-5.56)
Historical Mean Rainfall	-0.125	0.0689
	(-1.98)	(1.18)
Bus Stop in Village	0.107	0.542
	(1.21)	(2.33)
Bus Stop in Village * Rain per Day in 2011	-0.0452	-0.149
	(-1.38)	(-3.76)
Paved Road to Village	0.751	0.909
	(3.37)	(4.20)
Paved Road to Village * Rain Per Day in 2011	-0.0473	-0.222
	(-1.32)	(-7.58)
Bank in Village	0.431	0.167
	(2.15)	(0.71)
Bank in Village * Rain Per Day in 2011	-0.0568	0.0230
	(-1.37)	(0.38)
Male	0.307	0.310
	(9.89)	(9.93)
Observations	2,693	2,693
R-squared	0.327	0.337

Robust t-statistics, based on standard errors clustered by village-caste, in parentheses. All specifications include state fixed effects and control for education, age of respondent and a squared term in age, and 11 variables characterizing soil type, depth and drainage characteristics. All specifications also include 6 variables controlling for the proportion of village that are agricultural laborers or cultivators, and their interactions with rain per day, and proportion village laborers or cultivators that are eligible to receive insurance marketing.

Table 8: Village Fixed Effects Estimates: Demand for Kharif Season Labor by Cultivators (Cultivators with at least 1 acre)

	(1)	(2)	(3)	(4)
Dep. Var.:	Days of Harvest Labor Hired			
Sample:	Cultivators with at least 1 acre		Cultivators with at least 3 acres	
Offered Insurance in 2011	2.335	2.062	4.653	2.287
	(1.41)	(0.90)	(1.08)	(0.42)
Offered Insurance x Deviation of Kharif 2011 Rain per Day from Historical Average	1.070	1.163	3.355	4.234
	(2.48)	(1.84)	(3.37)	(3.42)
Offered Insurance in a Village where Payout Occurred		0.878		6.710
		(0.21)		(0.66)
Acreage Cultivated	2.327	2.328	1.660	1.665
	(2.30)	(2.29)	(1.68)	(1.68)
Observations	1,227	1,227	419	419
R-squared	0.412	0.412	0.401	0.401
Predicted Effect of Insurance Offer at Minimum Value of Rainfall Deviation (Negative Rainfall Shock)	-1.486	-2.094	-7.332	-12.84
	(-0.584)	(-0.507)	(-1.121)	(-1.411)
Predicted Effect of Insurance Offer at Maximum Value of Rainfall Deviation (Positive Rainfall Shock)	14.50	15.29	42.80	50.41
	(3.056)	(2.572)	(4.086)	(4.610)

Robust t-statistics, based on standard errors clustered by village-caste, in parentheses. All specifications control for village fixed effects and caste fixed effects.

Table 9: General Equilibrium Effects of Insurance Provision and Rainfall on Log Wages
(Landless Agricultural Wage Workers Ages 20+)

VARIABLES	(1)
Proportion Cultivators Offered Insurance in 2011	-5.290 (-3.20)
Proportion Cultivators Offered Insurance * Rain per Day in 2011 Kharif season	0.771 (4.68)
Proportion of Landless Labor Households Offered Insurance in 2011	2.508 (1.67)
Proportion of Landless Labor Households Offered Insurance * Rain per Day in 2011	-0.236 (-2.59)
Proportion of Households Offered Insurance in a Village where Payout Occurred	4.397 (6.33)
Rain per day during 2011 Kharif season	0.283 (2.07)
Rain per day during 2011 Kharif season, squared	0.0213 (2.87)
Historical Mean Rainfall	-0.154 (-4.35)
Bus Stop in Village	-0.293 (-2.96)
Bus Stop in Village * Rain per Day in 2011	0.0221 (1.14)
Paved Road to Village	2.487 (9.07)
Paved Road to Village * Rain Per Day in 2011	-0.387 (-8.72)
Bank in Village	-1.483 (-5.74)
Bank in Village * Rain Per Day in 2011	0.127 (4.87)
Proportion of HHs that are Cultivators * Rain per Day	-0.291 (-4.01)
Proportion of Village Households that are Cultivators	5.231 (6.83)
Proportion of HHs that are Landless Agri. Labor * Rain per Day	-0.238 (-4.45)
Proportion of Village Households that are Landless Agri. Laborers	4.180 (6.73)
Male	0.310 (9.93)
Proportion of village accounted for by largest caste	2.343 (4.52)
Total # of castes in a village	0.0503 (5.15)

Robust t-statistics, based on standard errors clustered by village-caste, in parentheses. All specifications include state fixed effects and control for education, age of respondent and a squared term in age, and 11 variables characterizing soil type, depth and drainage characteristics. All specifications also include 6 variables controlling for the proportion of village that are agricultural laborers or cultivators, and their interactions with rain per day.

Figure 1: Lowess-Smoothed Relationship Between Log Per-Acre Output Value and Log Rain per Day in the *Kharif* Season, by Insurance Treatment

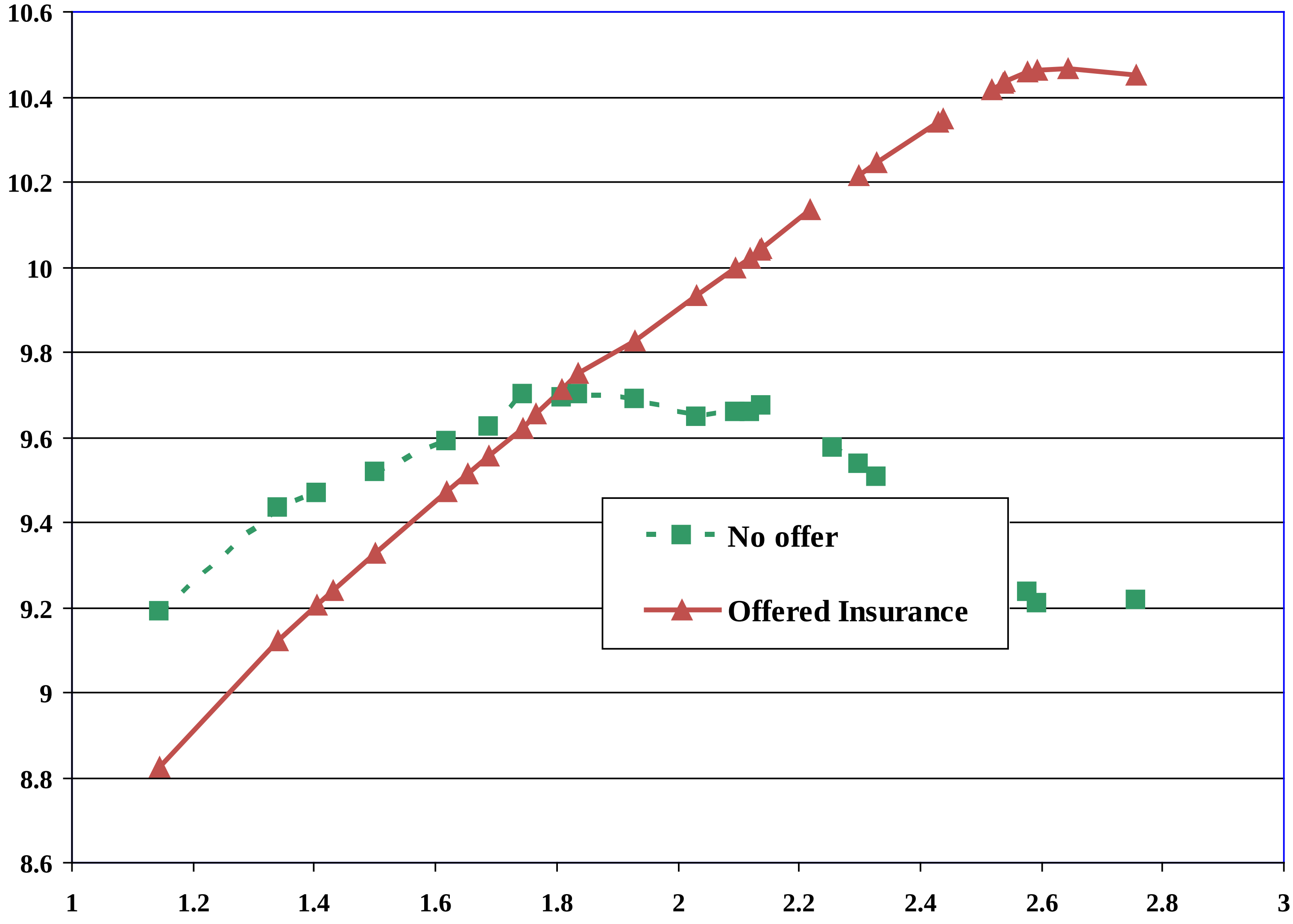


Figure 2: Timeline of Project Activities

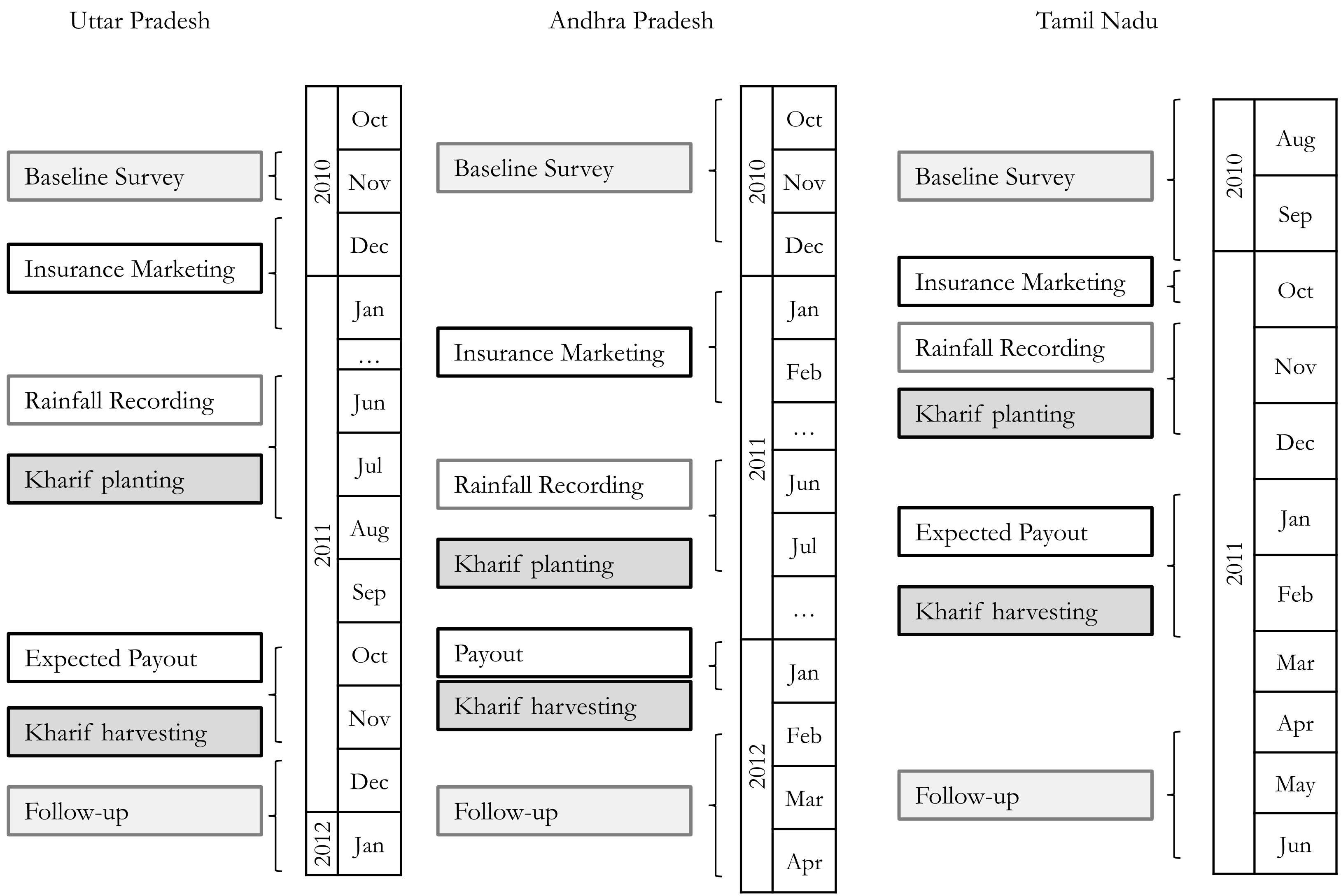
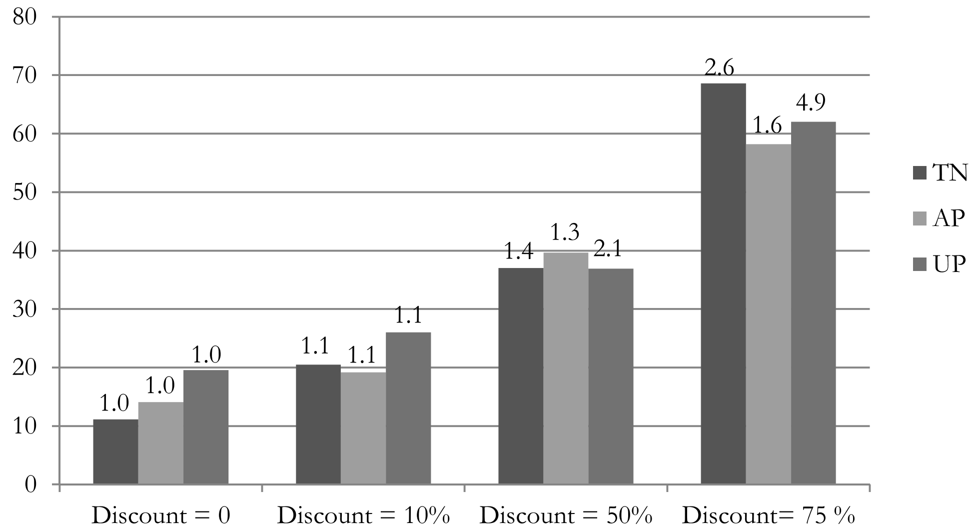


Figure 3: Rainfall Insurance Take-up Rates and Average Number of Policy Units Purchased



The height of the bars in the % of households who choose to purchase any insurance. The numbers on top of the bars indicate the average number of units of insurance purchased

Figure 4: Rain per Day in 2011 Kharif Season in Andhra Pradesh, by Rainfall Station

Insurance Payout Stations in Solid Black (with Rupee payout Amount)

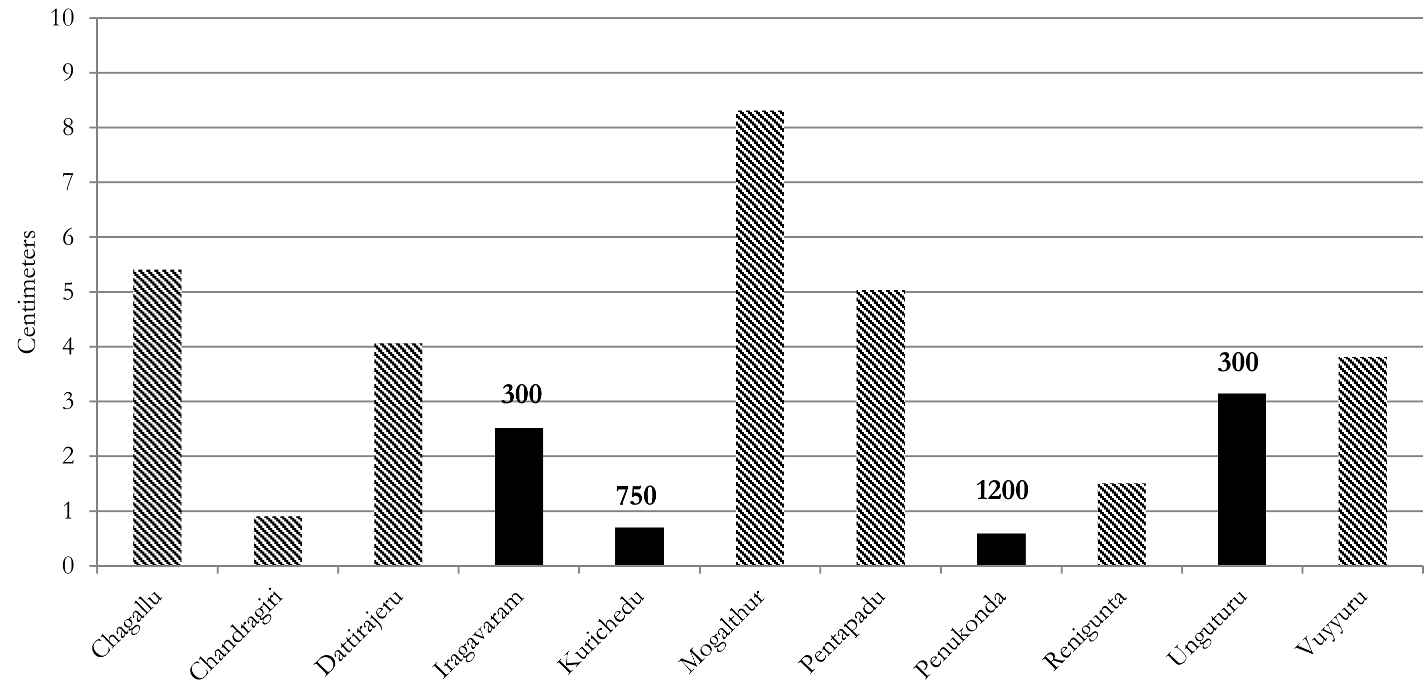
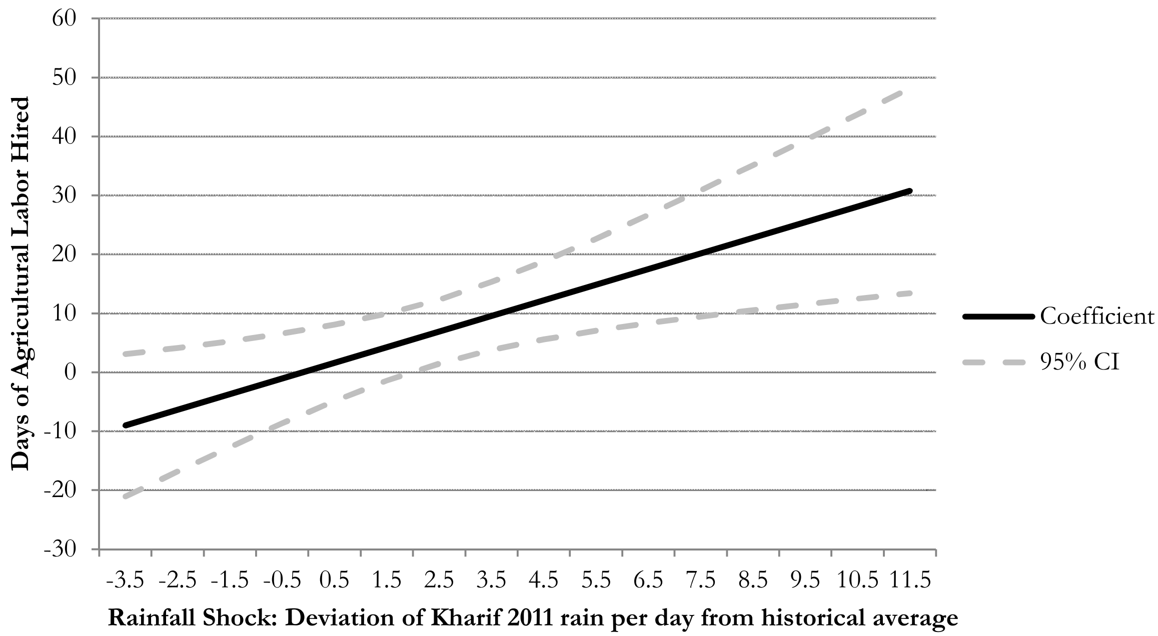
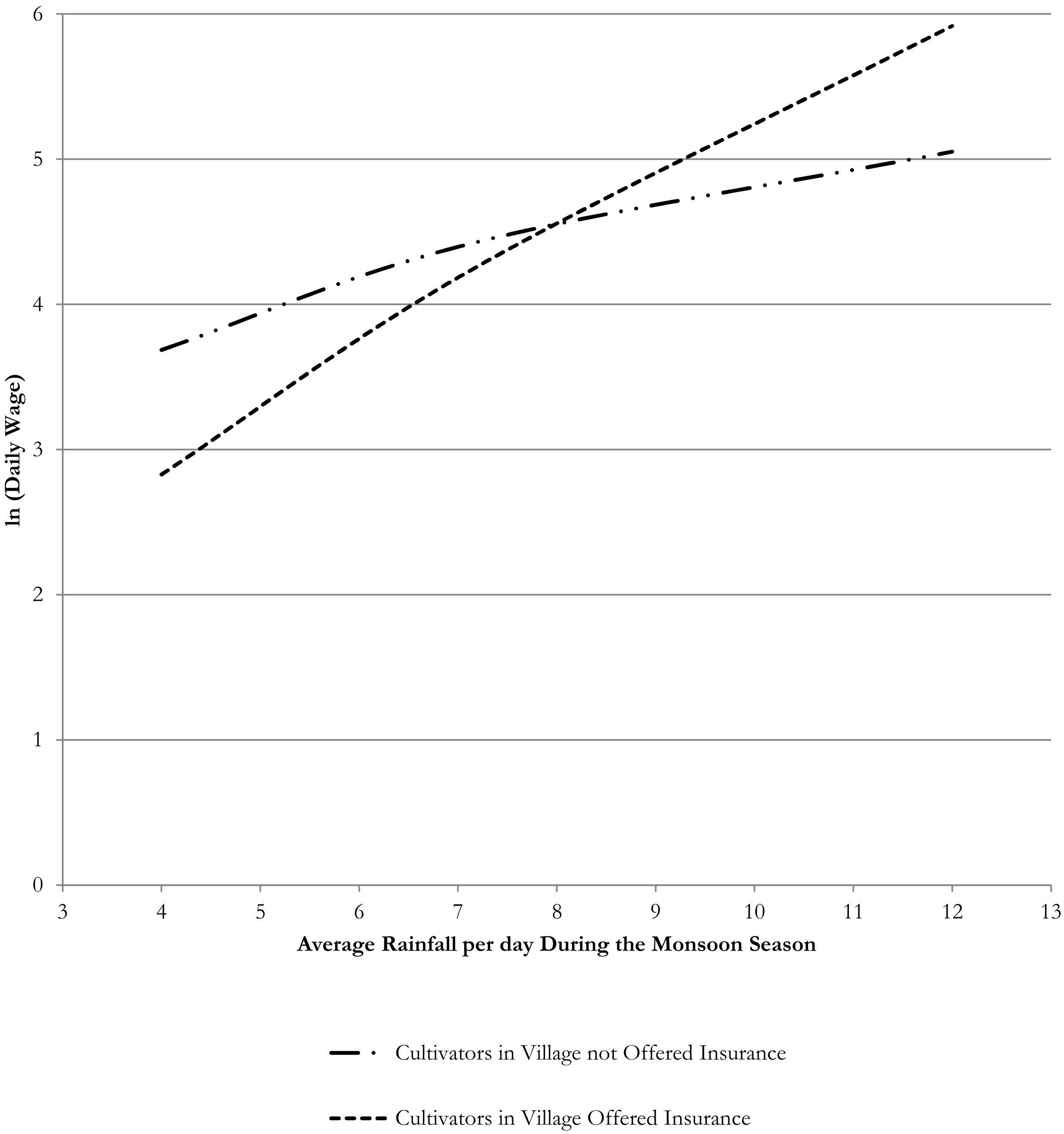


Figure 5: Predicted Effect of Insurance Offer on Cultivator Labor Demand



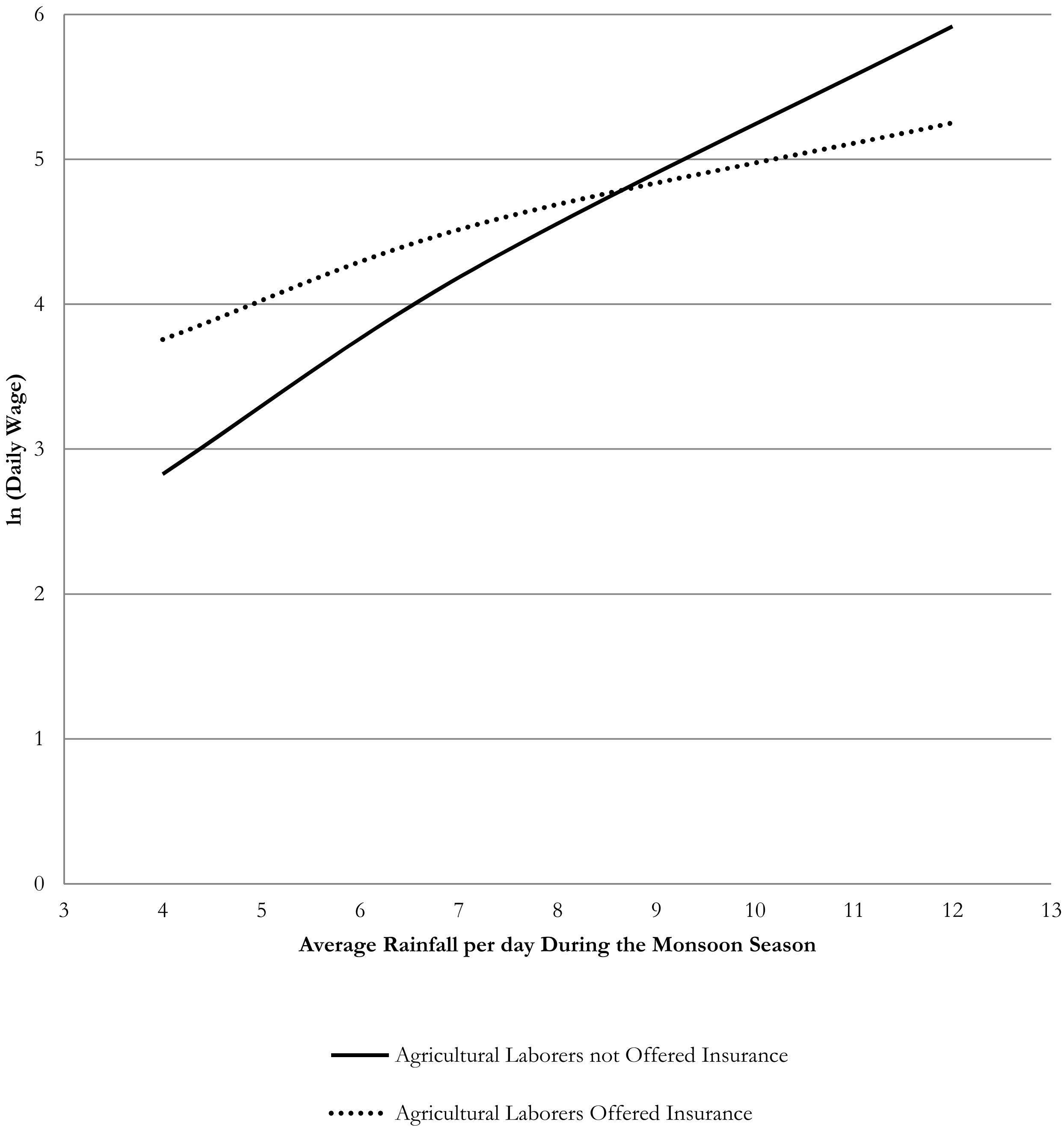
Note: Estimated values based on Table 4 Column 2.

Figure 6: Effect of Marketing Rainfall Insurance to Cultivators on the Equilibrium Wage Rate



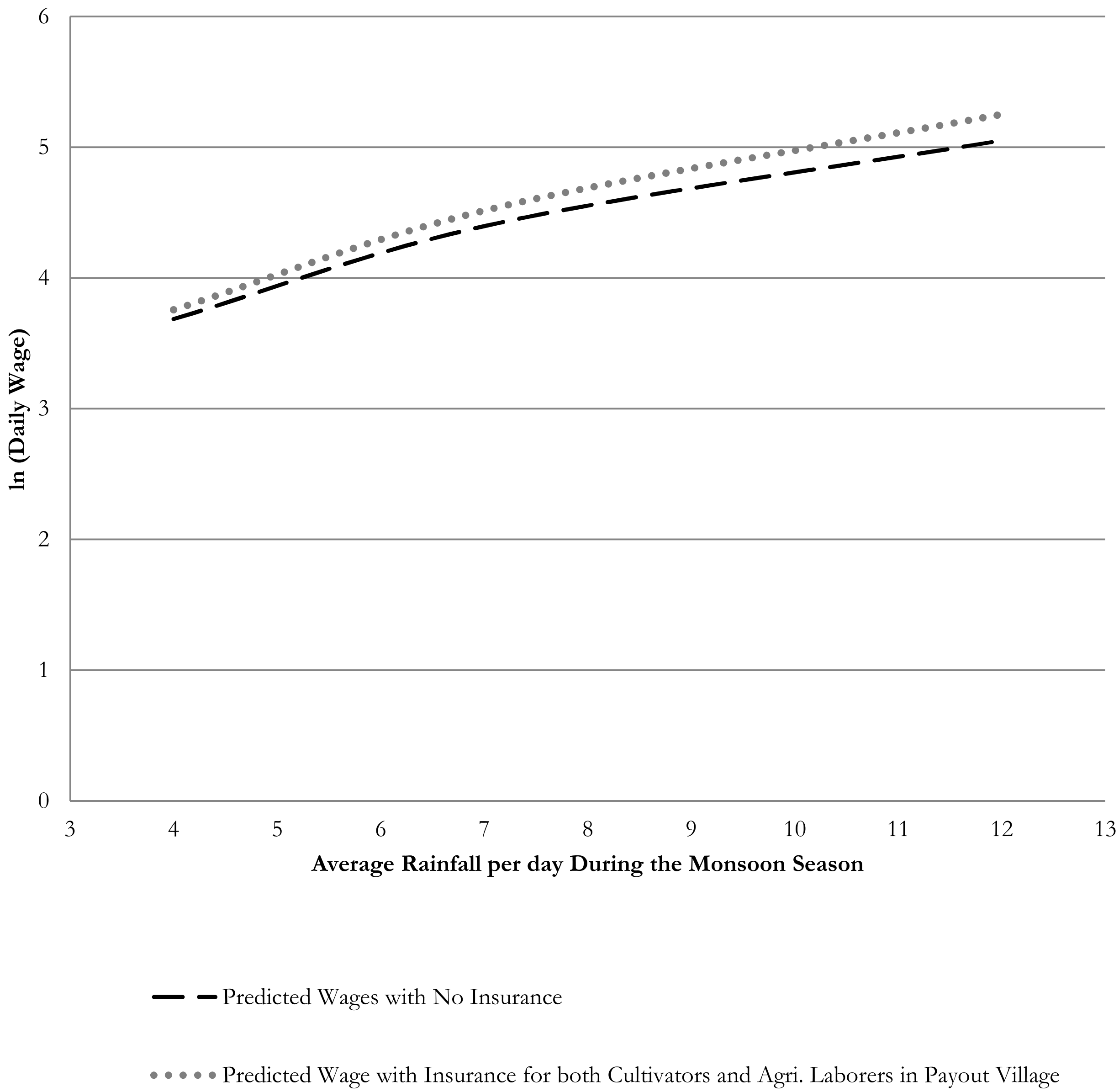
The wage rate is predicted based on the wage equation estimated in the first column of Table 4. Assumes an "average" village in terms of banks, roads, bus stops and fractions of cultivators and agricultural laborers in the populations, and that laborers do not receive insurance marketing. Graph is plotted for 2 standard deviations of rainfall per day around the mean.

Figure 7: Effect of Marketing Rainfall Insurance to Agricultural Laborers on the Equilibrium Wage Rate



The wage rate is predicted based on the wage equation estimated in the first column of Table 4. Assumes an "average" village in terms of banks, roads, bus stops and fractions of cultivators and agricultural laborers in the populations, and that cultivators receive insurance marketing. Graph is plotted for 2 standard deviations of rainfall per day around the mean.

Figure 8: Effect of Marketing Rainfall Insurance to both Laborers and Cultivators on the Equilibrium Wage Rate



The wage rate is predicted based on the wage equation estimated in the first column of Table 4. Assumes an "average" village in terms of banks, roads, bus stops and fractions of cultivators and agricultural laborers in the populations. Graph is plotted for 2 standard deviations of rainfall per day around the mean. The "insurance" line considers a case where the sample-maximum fractions of cultivators and agricultural laborers are offered insurance.