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Risk, Insurance and Wages in General Equilibrium

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Abstract

We estimate the general-equilibrium labor market effects of a large-scale randomized intervention in which we designed and marketed a rainfall index insurance product across three states in India. Marketing agricultural insurance to both cultivators and to agricultural wage laborers allows us to test a general-equilibrium model of wage determination in settings where households supplying labor and households hiring labor face weather risk. Consistent with theoretical predictions, 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 inducing changes in labor supply. Policy simulations based on our estimates suggest that selling insurance only to land-owning cultivators and precluding the landless from the insurance market (which is the current regulatory practice in India and other developing countries), makes wage laborers worse off relative to a situation where insurance does not exist at all. The general-equilibrium analysis reveals that the welfare costs of current regulation are borne by landless laborers, who represent the poorest segment of society and whose risk management options are the most limited.

JEL Codes: O17, O13, O16

Keywords: Index insurance, Agricultural Wages, General Equilibrium Effects

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1. Introduction

Field experiments providing weather insurance to farmers find, consistent with economic theory, that formerly uninsured farmers switch towards riskier, but higher-yield, crops and seed varieties (Cole et al 2013b; Mobarak and Rosenzweig 2014), thus making agricultural output more rainfall-sensitive (Karlan et al 2013; Mobarak and Rosenzweig 2013). Those cultivators hire landless laborers for harvest tasks, and changes in labor demand associated with cultivators' risk-taking can make wage rates more volatile. Insurance sales to cultivators can thus potentially worsen the welfare of landless laborers – the poorest of the poor who presumably find it most difficult to manage risk, and who make up a sizeable proportion of the world's impoverished population. On the other hand, if greater risk-taking by cultivators is associated with higher average yields, then average wages may rise. To properly evaluate the welfare effects of introducing a formal insurance product in a developing country, it is important to move beyond effects on the treated population, and determine the general-equilibrium effects on both wage levels and the sensitivity of wages to rainfall variability.

In this paper we examine the general-equilibrium labor market effects of a large-scale randomized controlled trial (RCT) that marketed rainfall insurance to both landless and cultivating households in rural India. Based on a simple model of the agricultural labor market, 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 fluctuations in wages. Further, our analysis

[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 introduce some idiosyncratic component of risk for cultivators, whereas all agricultural laborers of the same gender face the same wage rate.

shows that selling insurance only to cultivators makes the landless worse off via general-equilibrium wage effects, compared to a regime of no insurance.[3]

Our research contributes to a burgeoning literature on the effects of insurance marketed through RCT's[4] by tracking the labor market spillovers of such interventions using a general equilibrium model. General-equilibrium effects are important to consider for other interventions being tested using RCT's in the large and expanding program evaluation literature (Heckman 1991; Rodrik 2009). 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, providing migration opportunities (Bryan *et al.* 2013) may change wages at the destination, and providing livestock assets (Bandiera *et al* 2013) or access to credit (Karlan and Zinman 2010; Banerjee *et al* 2013) may affect market prices. Comprehensive evaluation of development programs requires a full accounting of these general-equilibrium changes, especially if we are interested in assessing how effective an intervention will be when it is scaled up (Acemoglu 2010)

Our study is the first to analyze the aggregate, general equilibrium effects of any experimental intervention on both average wages and its volatility. Furthermore, we present experimental evidence on the labor demand and supply mechanisms by which these wage-effects are realized. A few studies have considered spillovers effects of interventions on the non-treated (Miguel and Kremer 2004, Angelucci and DeGiorgi 2009, Crepon et al 2012), others have examined peer effects in technology adoption (Kremer and Miguel 2007, Oster and Thornton 2012, Miller and Mobarak 2013), and yet others have tracked political economy responses to interventions (Bold et al 2012, Guiteras and Mobarak 2013). But these spillover effects are mostly related to non-market

[3] We marketed rainfall index insurance (a contract which pays out if the monsoon is delayed) to landless agricultural wage workers, in addition to selling insurance to cultivators in the same villages. 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. We stratified the randomization by these two occupational groups in order to study both the labor demand and the labor supply responses to insurance sales.

[4] 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).

mechanisms, such as health externalities, direct transfers and information flows. Muralidharan and Sundararaman's (2013) experimental study of school vouchers in India estimates aggregate effects in relevant markets, but does not estimate price or (teacher) wage effects. Our study is distinct because the spillover effects we identify work through the aggregate effects of equilibrium price changes that are the consequence of any scaled-up intervention.[5]

Our research also contributes to the small 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), the role of imperfect credit markets on wage volatility (Jayachandran 2006), and nominal wage rigidity with uninsured shocks (Kaur 2012). Our work in particular builds on that of Jayachandran (2006), who was the first to show that market imperfections, in her case for credit, have general-equilibrium effects on rural wage levels and volatility, working through labor supply and migration channels. Here, we focus on uninsured risk and we test the model of risk and insurance using variation derived entirely from a randomized field experiment large enough to detect general-equilibrium effects.[6] Use of randomized variation limits concerns about omitted variables bias and other threats to identification. Further, our experimental design allows us to examine the precise labor supply and labor demand mechanisms by which insurance affects wages.

[5] There are related non-experimental studies on general equilibrium effects of credit market imperfections on wages (Jayachandran 2006) and on technology diffusion and price dispersion (Jensen 2007, Aker 2010).

[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).

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, random variation in the *fractions* of cultivators or laborers in a village receiving offers, and random 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. We generate cross-village variation in these variables of interest through a two-step feature of our experimental design – we first randomly select a subset of castes (with varying population sizes) in each village to receive insurance marketing, and then offer random subsets of households within these castes rainfall insurance contracts.

Consistent with the theoretical predictions, we find that insured cultivators take more risk, and labor demand therefore becomes more rainfall-sensitive. On the other hand, insured agricultural wage workers supply less labor when insurance payouts occur. In villages that qualified for a payout (i.e. where the monsoon was delayed), they 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). Wages are also higher when a larger fraction of households are offered insurance in villages that ultimately qualified for a payout (the labor supply effect). Policy simulations based on our estimates suggest that landless wage workers would 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.* 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 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 follows, 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 we ignore credit constraints in the model, so that the effects of risk are transparent.[7] Cultivator and landless households can save (at a fixed interest rate *r*) and borrow.

We begin with the labor supply decision made by the landless. To focus on the role of risk, we ignore the smoothing problem highlighted by Jayachandran (2006) and employ a one-period labor-leisure model. 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 $j = H \; or \; L$ denotes the state of nature. The *L*-state occurs with probability q. We consider two groups of landless, corresponding to our RCT – one group which is able to purchase insurance optimally at 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.)

[7] In the empirical work we allow for credit constraints, employing in our equilibrium wage specification the same variables used by Jayachandran (2006) in her tests of credit constraints and also carry out a test for credit constraints on cultivator harvest labor demand.

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*, the non-earnings income of the insured is greater than that of the uninsured because of the insurance payout. Labor supply of the insured is lower than that of the uninsured, because leisure is a normal good. In the high-state *H*, 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. 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*. Insurance payouts were large when they occur, and our empirical exercise will therefore concentrate on labor supply effects in villages that qualified for a payout.

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 using a Cobb-Douglas technology with two inputs, *l* (labor) and x (an input like fertilizer or seed variety that is complementary with rainfall). In stage 1 (planting-stage), cultivators decide on the stage-1 input x and whether to buy insurance. In stage 2, the state of nature θ^j is realized, labor is hired and profits are maximized. Stage-2 profits are $\theta^j l^\beta x^{(1-\beta)} - w^j l$, where l is hired labor. Thus, in any state j, labor demand is

$$l = x\left(\frac{\beta\theta^j}{w^j}\right)^{\frac{1}{1-\beta}}$$

The stage-1 program is:

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

$$c_1 = m - x - s - pI$$

$$c_2^j = rs + \theta^j l^\beta x^{(1-\beta)} - w^j l + i^L I$$

where i^L is an indicator variable for the low state, when the insurance payout occurs.

As noted, we allow borrowing and savings (*s*), where *r* is the return on savings. We ignore the use of labor in the first 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 x and labor in that stage.

It is easy to show that in the absence of insurance the amount of x is lower than the amount that maximizes expected profits, due to risk, and that the amount of the stage-1 input increases as the cost of insurance falls; i.e., insured cultivators invest more than uninsured cultivators. This follows from the fact that purchasing insurance decreases cultivator marginal utility in the low state while increasing x decreases marginal utility in the high state. More generally, insured cultivators will select inputs that increase output more in the high state than in the low state compared to the uninsured, because insurance payouts occur in the low state. Our empirical exercise will therefore compare stage-2 (harvest stage) labor demand for insured and uninsured cultivators, and how that demand varies across rainfall states.

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

$$[1-\gamma-\gamma\frac{y^j}{w^j}]N = [x\left(\frac{\beta\theta^j}{w^j}\right)^{\frac{1}{1-\beta}}]M$$

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 Δw.

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

$$\frac{dw}{dy} = \frac{\gamma(\beta-1)w}{\gamma y(\beta-1) - lw\left(\frac{M}{N}\right)} > 0$$

From Table 1, labor supply is lower in state L 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, 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.

Proposition 3: Offering insurance to cultivators increases wage volatility (Δw).

Proof: Insured cultivators use more first-stage inputs x (inputs more complementary with rainfall). The effect of an increase in x on wages in the H state is higher than in the L state, so $\frac{d\Delta w}{dx} > 0$.

$$\frac{d\left(\frac{dw^j}{d\theta^j}\right)}{dx} = \frac{d\left(\frac{dw^j}{dx}\right)}{d\theta^j} = \frac{-w\gamma y(\beta-1)\beta\left(\frac{\beta\theta^j}{w^j}\right)^{\frac{\beta}{1-\beta}} MN}{wx\beta\left(\frac{\beta\theta^j}{w^j}\right)^{\frac{1}{1-\beta}} M - \gamma y(\beta-1)N} > 0$$

Offering insurance only to cultivators increases wage volatility and thus may worsen the welfare of the (uninsured) landless.[8] On the other hand, it may also provide some benefits to the landless:

Proposition 4: Offering insurance to cultivators increases average wages.

Proof: Insured cultivators use more x. The effect of an increase in x on the equilibrium wage in any state is positive

$$\frac{dw^j}{dx} = \frac{\left(\frac{\beta\theta^j}{w^j}\right)^{\frac{1}{1-\beta}}(\beta-1)(w^j)^2 M}{\gamma y^j(\beta-1)N - xw\left(\frac{\beta\theta^j}{w^j}\right)^{\frac{1}{1-\beta}} M} > 0$$

To summarize, offering insurance to cultivators makes labor demand more volatile across rainfall states because insurance allows cultivators to make decisions that increase output in the high state, while worrying less about outcomes in the low state when payouts are expected. Accordingly, the sensitivity of wages to rainfall also increases when a larger number of cultivators are insured. Insured cultivators also invest more, and average wages therefore rise. On the other hand, insurance to landless workers dampens wage volatility, because insured workers supply less labor than the uninsured when the rainfall is bad (i.e. when they receive insurance payouts). Our empirical work will examine: (a) how cultivator labor demand responds to insurance offers, across rainfall states; (b) how agricultural worker labor supply respond to insurance offers, across rainfall states; and (c) how equilibrium wages respond to the fractions of cultivators and workers insured, across rainfall states.

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[8] 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 the insured: profits are higher in the low state compared to the case where no cultivator insurance is available.

3. Experimental Design

3.1 Sampling

The National Council of Applied Economic Research (NCAER)'s 2006 Rural Economic and Development Survey (REDS) conducted a comprehensive listing of all rural households residing in 202 sampled villages in 15 major Indian states. 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.

Our sampling procedure first eliminated members of all castes (*jatis*) with fewer than 50 households in the listing for these 63 villages.[9] 118 unique *jatis* met this size criterion in the REDS listing. We randomly select 42 (of 63) sampled REDS villages in the three states to receive insurance marketing. Our next step was to randomize insurance offers to households within these 42 villages. We stratified the randomization by caste, and members of 25 (out of 118) castes were randomly selected to not receive any insurance offers. Since the randomization was stratified by village and caste, we will cluster our standard errors by caste-village groupings in all our regressions. Within the 93 treatment castes, we used occupation data from the 2006 REDS listing to target insurance offers to 2400 cultivator households (i.e. those with land, making cultivation decisions and typically hiring in labor) plus 2400 "pure" agricultural labor households (households purely reliant on agricultural wages, with no member engaged in cultivation). The insurance product was successfully marketed to 4667 households between October 2010 and January 2011, with a take-up rate of 42%. 98% of these households had no prior exposure to formal insurance.

3.2 The Insurance Marketing Experiment

There are three sets of variables created by the randomized design that are important for testing the implications of our model and for identifying general-equilibrium effects. The first is

[9] This is because another project (Mobarak and Rosenzweig 2014) required us to construct average *jati* characteristics with statistical precision, which led to our focus on castes that were relatively populous in these specific villages.

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. Using this variation we can compare, for example, the labor demand of cultivators randomly selected to receive an insurance offer – i.e. the 'intent-to-treat' - against cultivators randomly chosen to not receive the insurance offer. The model suggests that insurance should make labor demand more sensitive to rainfall, and the specifications therefore add interaction terms between insurance offers and rainfall realized during *Kharif* 2011, after insurance offers are made.

Insurance offers were subsidized in our experiment to ensure adequate take-up, thereby enabling a study of the effects of insurance. Although we report intent-to-treat estimates throughout the paper, we randomly varied the extent of the subsidy. The price for a unit of insurance varied from Rs 80 to Rs 200 (USD 1.6 - 4) across villages, with an average price of Rs.145. The experiment offered 0%, 10%, 50% or 75% discounts on this price, and Figure 1 shows that most of the insurance was purchased at highly subsidized rates. Buying insurance and not receiving a payout is therefore unlikely to have had a significant (negative) wealth effect in this setting, which is relevant for testing the labor supply predictions of our model.

3.3. Insurance Payouts

In contrast, the second variable useful for testing implications of the model - the occurrence of an insurance payout, induced by random variation in the realization of rainfall in 2011 – was potentially a large positive wealth shock to those who purchased insurance. 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.[10] The three trigger dates varied across villages. In many villages, the first (Rs.300) payout came if the monsoon was about 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}. This is an index product where all farmers in the village would receive the same payout (or not).

Four villages in Andhra Pradesh (AP) qualified for a payout. 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 2 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 the payout indicator separately from a measure of rainfall amount.

For our empirical tests of labor supply decisions, it is important to establish that the occurrence of a payout is a random shock, that long-run rainfall conditions in the payout villages do not different systematically from those in non-payout villages. If, instead, the occurrence of a payout indicates that these villages are generally more susceptible to large rainfall shocks, then farmer behavior in such villages may be systematically different. In principle, this should not be the case, 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 attempted to keep the unit price of insurance as similar as possible across villages, and the trigger dates were therefore adjusted

[10] 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.

to keep payout probabilities constant. Even though in principle none of this should be of concern to the estimation strategy, we can examine the historical rainfall data to directly establish that rainfall conditions are not systematically different across payout and non-payout villages.

The REDS survey collected historical rainfall data in all our sample villages for the period 1999-2006. Using these data, we compute the historical mean rainfall during the *Kharif* season in each village, and the inter-annual coefficient of variation of that rainfall. Table 2 reports these moments of the rainfall distribution, and a t-test of differences across the payout and non-payout villages. First 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. 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.

In summary, payout villages 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. We will therefore treat the occurrence of payouts as a random shock in our regressions. Moreover, we will control for historical mean rainfall in all our equations, and our rainfall measure will use only the variation stemming from the deviation of 2011 *Kharif* season rainfall from its historical mean.

3.4 Village-Level Variation in Insurance Marketing

A third set of variables useful for identifying general-equilibrium effects is cross-village variation in the proportion of cultivators or agricultural laborers who received insurance offers. According to our model, labor supply and labor demand in the village depend on access to insurance by wage workers and cultivators in the aggregate, and these factors will therefore affect equilibrium wages in agriculture.

Stratification of the random assignment by caste (described above) creates natural variation in the number and fraction of farming households in each village receiving insurance offers. For example, one of the 93 castes randomly chosen for treatment may have been relatively populous in village A but sparse in village B, whereas the dominant caste in village B may have been randomly assigned to be a 'control caste' not receiving the insurance treatment. The fractions of cultivators and agricultural laborers receiving insurance offers would be greater in village A under this scenario.

About 25% of all cultivators and 31% of all laborers received insurance marketing in the average treatment village, but these fractions vary between 0% to 53% for cultivators, and between 0% to 100% for laborers. For estimation of the general equilibrium wage equation, it is important to establish that this variation can be treated as random. The main concern arises because we eliminated all "small castes" (with fewer than 50 members in the REDS listing) from our sample frame, and this reduces the numerator (number of insurance offers) 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 and other factors like the number of castes in the village or the concentration of caste membership, because the fraction of farming households *eligible* to receive insurance marketing (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 eligible population according to our sampling rule.

A closely related concern, since 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 eligible to receive insurance separately from the fraction of landless laborers who are eligible. Furthermore, we will condition on the population shares of cultivators and laborers, and rely only on variation in the subsets of those cultivators and laborers who were randomly assigned to receive insurance offers.

Table 3 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. Column 1 reports the correlations between the fraction of the population *eligible* to receive insurance marketing, 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. Column 3 reports the correlations between our variables of interest and village and caste characteristics *conditional on* the fraction of cultivators or laborers eligible to receive insurance marketing, and all the correlations become small and statistically insignificant.[11] In the fourth column of Table 3, we again examine the correlation between our variables of interest and village and caste characteristics conditional on state dummies, fraction of population eligible to receive insurance marketing, *and* population shares of cultivators and laborers. The correlations remain statistically insignificant, and close to zero. This exercise, coupled with careful consideration of the details of our sampling

[11] We regress 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.

strategy, indicates that the proportion variables can be treated as exogenous, conditional on the sampling eligibility variables that we will control for in our regressions.

4. Data

We collected follow-up data after the *Kharif* harvest, starting in April 2011 in Tamil Nadu, and between December 2011 and March 2012 in Uttar Pradesh and Andhra Pradesh. The follow-up sample comprised of all households we marketed insurance to, plus an additional 1619 control households selected from the same sampling frame. 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. For landless wage workers, our survey asked questions about the number of days of labor supply, total earnings and the wage rates received. Agricultural wages in rural India vary by gender and age (and possibly education), and we collected information on these demographic factors from all respondents. The results we report below are similar, regardless of whether we use wage rates directly reported by respondents, or infer the wage rate on the basis of reported earnings and days worked.

Table 4 provides summary statistics on the variables used for analysis in three samples: (1) Cultivators who own more than half an acre 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, useful for the wage estimation. About 60% of all cultivators and agricultural wage workers in our sample villages were offered the rainfall insurance product, and high market penetration allows us to track general equilibrium effects on wages. There is significant rainfall variation across villages, and large rainfall shocks experienced in 2011: Historically, these villages receive 4.15mm of rainfall per day, but the average rainfall deviation in 2011 was 3.38mm per day. 14-15% of our total sample were exposed to insurance payouts. Daily agricultural wages averaged Rs. 120, but males earned more.

Table 4 shows that only 2.3% of wage workers out-migrate during the *Kharif* season, and we will therefore focus on labor supply within the village in our estimates. Migration outside 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 at the end of the *Kharif* to collect accurate agricultural data, but we have data on the same variables that Jayachandran (2006) used to proxy for the ease of migration: the presence of bus stops and paved roads in the village. The wage estimates will directly control for these migration variables, while the labor supply and demand estimates will include village fixed effects to control for all time-invariant village characteristics including ease of migration.

5. Empirical Methodology and Results

5.1 Labor demand

The key implication of the model for labor demand is that insured cultivators will use more inputs that are complementary with rainfall compared with uninsured cultivators. As a result the output of the insured will be higher in higher rainfall states than that of the uninsured, and we should observe that more labor is employed for harvesting. In other words, the elasticity of labor demand with respect to rainfall should be higher 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, 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 village-specific rainfall shock experienced in the village during the season; $\boldsymbol{K}_k$ is a vector of village dummy variables; and ε^1_{jk} is the error term. Standard errors are clustered by caste-village groupings in all regressions, since the randomization of insurance offers was stratified at this level.

The set of village indicators absorb all differences across the villages in *Kharif*-season realized and historic rainfall as well as input prices. β_1 is thus the estimated linear intent-to-treat (ITT) effect of insurance (offers) on harvest labor demand and β_2 is an estimate of how labor demand varies with rainfall net of wages 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 first column of Table 5 reports the estimates of the harvest labor demand equation for cultivators with at least .5 acres of land. Consistent with the theory, 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 a one standard deviation increase in rainfall, for given historic mean rainfall, increases harvest labor demand by 3.3 days more for insured compared with uninsured cultivators - a 22% increase in relative demand. Consistent with uninsured farmers behaving more conservatively than insured farmers, the negative β_1 coefficient, while not statistically significant, implies that at very low rainfall levels harvest labor demand is higher on uninsured compared with insured farms.

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, and thus substantially after the planting stage concluded.[12] 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. We cannot reject the hypothesis that the payouts had no effect on labor demand. The insurance rainfall sensitivity coefficient remains unchanged 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. 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 labor days. This category of labor demand includes labor used for sowing, soil preparation and transplanting. Column three shows that in contrast to the estimates for harvest labor, the effect of realized rainfall in the village on the difference in demand for planting-stage labor across insured and uninsured cultivators is not statistically different from zero. Indeed, 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 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.

5.2. 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 worker households aged 25-49. We estimate the following specification for a member i in landless household j in village k:

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

$$L_{ijk}^{S} = \alpha_1 I_{jk} + \alpha_2 (I_{jk} \cdot R_k) + \alpha_3 (I_{jk} \cdot r_k) + \boldsymbol{Z}_{ijk}\pi + K_k + \varepsilon_{ijk}^{2}$$

The first two columns of Table 6 examine the determinants of participation, where L^{S}_{ijk} is an indicator for households that supply any agricultural labor hours at all during the *Kharif* season. The dependent variable for the last two columns is the number of days spent in the agricultural labor market during the season. I_{jk} is again the indicator for randomized insurance offers, and R_k is the rainfall shock for *Kharif* 2011, relative to historical mean rainfall. $\boldsymbol{Z}_{ijk}$ is a vector of person-specific characteristics (age, age squared and gender); and $\boldsymbol{K}_k$ is a vector of village indicator variables; and ε_{ijk}^{2} is the error term. The village dummy variables absorb all differences across villages in realized and historic rainfall and other determinants of labor supply at the village level. Standard errors are again clustered by the unit of randomization (caste-village groupings).

Our model (Proposition 1) predicts that the labor supply responses to insurance will differ depending on whether payouts occur. In the low-rainfall state, when payouts occur, the insured are predicted to supply less labor than the uninsured, due to the income effect of the payout (1a). This prediction reverses in the high rainfall states (1b) if purchasing insurance and not receiving a payout leads to a substantial negative wealth effect.

To test the model's predictions, we therefore estimate the labor supply equation separately in Table 6 for villages with and without insurance payouts. As we show in Table 2, the permanent rainfall conditions across these two sets of villages is similar, and payout villages just happened to have a negative rainfall shock in 2011. Moreover, our inclusion of village fixed-effects means that all contrasts between the insured and the uninsured are within-village. Specifically, Table 6 provides the ITT estimates for the labor supply behavior of households that received random insurance offers relative to same-village residents who did not receive offers. 40% of those who were offered insurance purchased insurance, and they received substantial payouts in the villages that qualified for payouts, leading to significantly higher non-earnings incomes than the uninsured during the peak harvest stage of production. Proposition 1a therefore predicts $\alpha_1<0$ and $\alpha_2<0$, i.e. that the insured work less, and their labor supply is less sensitive to realized rainfall.

There was no such wealth effect in the villages that did not qualify for a payout. While the insured paid some premiums, Figure 1 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 in the payout villages (which ranged from Rs. 300 to Rs. 1200 per unit). The model predicts reverse labor supply effects if there is an adverse wealth effect from paying the premium in non-payout villages, but in reality there was not much of a wealth effect, in contrast to the payout village sample.

The first column of Table 6 shows that both $\alpha_1<0$ and $\alpha_2<0$ in the sample of villages that received payouts, implying that landless labor households offered insurance are significantly less likely to participate in the agricultural labor market at any level of rainfall. Using the point estimates, we compute the derivative of their *ex post* harvest-period labor supply with respect to insurance offers at the median value of the rainfall shock in the payout village sample (1.9 mm's below the per-day mean). The estimates (and t-statistic) reported in the bottom row indicates that the participation rate of insured laborers after receiving payouts was 28.5 percentage points lower than that of otherwise identical laborers in households not offered insurance.

In contrast, insurance offers do not affect labor force participation in the villages that did not receive payouts. The bottom row of the second column shows at the median rainfall shock in this sample, there is no statistically significant difference in the labor supply of the insured and uninsured. This is consistent with the subsidized insurance contract having only a marginal impact on the non-earnings income of the landless households.

In the third and fourth columns of Table 6 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, though less precisely estimated, for the intensive margin of labor supply. Both $\alpha_1<0$ and $\alpha_2<0$ in the payout sample, indicating that the insured who received payouts work fewer days than the uninsured at any level of rainfall, but both coefficients carry a t-statistic of 1.83, which implies that they are only significant at the 10% level. The point estimates indicate that at the median level of rainfall shock, those offered insurance worked approximately 15 days less during the *Kharif* season. Paralleling the participation results, the insured in the non-payout villages supplied no less labor than the uninsured (point estimate of -4.6 days, and not statistically significant).

5.3 The General Equilibrium Wage Equation

The labor market equilibrium condition in the model relates wage volatility across rainfall states to the fractions of cultivators and wage workers who are insured. 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). This is because of the labor supply mechanism in which wage workers supply less labor in bad rainfall states (when they receive payouts) when they are insured, and more labor in high rainfall states when they don't receive payouts. Our labor supply estimates showed that this mechanism operates in the payout villages, where the wealth effect from insurance payouts is substantial. We will now test the aggregate effects of these demand and supply mechanisms by estimating a general equilibrium wage equation:

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

W_{ik} is the daily wage rate reported 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 the fraction of landless laborers who received randomized insurance offers, IP_k the fraction of households offered insurance in payout villages. The RHS variables of interest that help us test the general equilibrium predictions of the model are:

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 more insurance for cultivators increase wage volatility across rainfall states, which would support Proposition 3.

b) The interaction between LI_k and r_k. A negative coefficient (γ_4) on this interaction would imply that more insurance for wage workers decrease wage volatility across rainfall states, which would support Proposition 2.

c) A positive coefficient on IP_k (γ_5) would imply that landless laborers supply less labor when insurance payouts occur, and this raises village level wages.

We focus on these predictions, while controlling for $\boldsymbol{Z}_{ik}$, a vector of person-specific determinants of wages, such as gender, age, age-squared and indicators for primary and secondary school attainment. This is primarily why we estimate the wage equation with individual-level data: we gain precision and efficiency by soaking up the unnecessary variation in wages with its individual level determinants. For example, the estimated coefficient on gender in the wage equation (Table 7) shows that males earn 30% more than females. Controlling for these quantitatively important determinants of wages using individual-level data leads to greater statistical power.

We also control for a large vector of village-level characteristics, $\boldsymbol{V}_k$. This vector includes the sampling variables (proportion of cultivators and laborers who were eligible to receive insurance offers in our sampling strategy), and the proportion of cultivators and laborers in the population, so that – as discussed in detail in section 3.4 – the coefficients of interest are identified using purely random variation in the fractions of cultivators and laborers who were offered insurance in the experiment. We also control for 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 r_k identifies the effect of the 2011 rainfall shock. Further, we control for eleven different soil type variables including soil color (red, gray, black), type (soft or hard clay), percolation speed, depth and drainage characteristics.

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 lead 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). 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.

5.4 Estimation Results on General Equilibrium Wages, and Policy Simulations

Results from estimating the general equilibrium wage equation are shown in Table 7. Wages are logged so that coefficients can be interpreted as percentage changes. 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 equation from the existing literature (Jayachandran 2006) and establish that wage-setting in our sample of villages is not unusual, and conforms to what Jayachandran finds using a sample of districts across India. We replicate the main results of her study in our sample of villages: wages are substantially higher in villages with banks, paved roads and bus stops, and the presence of any of these three types of credit or migration infrastructure (all of which offer better income smoothing opportunities) reduces the sensitivity of wages to rainfall variation. Migration during the *Kharif* season is quite rare in our sample, but the infrastructure variables allow us to control for village-level differences in the propensity to migrate in the off-season. Wages are 14.5% greater for every extra millimeter per day of a positive rainfall shock, but the coefficient on the square term in r_k indicates that the positive marginal effect of rainfall tapers off as the village experiences a larger and larger rainfall shock.

In the second column of Table 7 we add the insurance variables of interest. First, we find evidence consistent with Proposition 3: $\beta_2>0$, which implies that offering insurance to a larger proportion of cultivators in the village increases the volatility of wages across rainfall states. This mirrors the labor demand results we showed in Table 5 – these wage effects presumably arise because when rainfall is good, insured cultivators hire more harvest labor than uninsured cultivators. Furthermore, $\beta_1<0$ and highly significant, which implies that during droughts, wages actually fall even further in villages where many of the cultivators are insured. These two results are consistent with cultivators taking more risk when insurance is offered. They have a bumper harvest under good rainfall conditions and therefore hire more harvest labor, but suffer larger losses during droughts (when they expect insurance payouts), and cut back on hiring labor under such conditions even more than the uninsured. The results also clearly show the adverse spillover effects on landless laborers of selling insurance to cultivators. Wages become more volatile, and the landless are worse off, especially if they are uninsured. In terms of magnitudes, a 10% increase in the fraction of cultivators 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. According to these estimates, insurance for cultivators leads to substantially greater wage volatility.

Second, we find evidence consistent with Proposition 2: $\beta_4<0$, which means that offering insurance to a larger proportion of cultivators in the village decreases the volatility of wages across rainfall states. 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 find a general equilibrium effect consistent with that mechanism. Our results show that $\beta_5>0$, 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 in payout villages increases the wage rate by 24.7%. In summary, insured laborers supply less labor than the uninsured when they expect payout. This increases the wage rate, and helps to indirectly insure the uninsured laborers in the same village.

These general equilibrium 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 3 plots the predicted wage-rainfall relationship based on the general equilibrium 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 maximum fraction receiving insurance marketing in any of our sample villages. For this simulation we assume that landless laborers do not receive insurance, because this reflects real-world insurance marketing conditions – the landless typically do not have the have the opportunity to purchase agricultural insurance. 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 entire range of rainfall observed across our sample villages, which is roughly two standard deviations around the mean rainfall per day.

Figure 3 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 0.63 log points lower. At the median level of rainfall experience in our sample in 2011, wages decrease by 0.23 log points. The effect turns positive at the 54th percentile of rainfall, and at the 70th percentile of rainfall village wages are 0.34 log points higher. The key lesson from this simulation is 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 wages.

Next we simulate the effects of insurance for landless agricultural laborers on village wages based on the same general equilibrium estimates. Figure 4 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 maximum fraction receiving insurance marketing in any of 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% 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 responses by workers in the payout villages.

Figure 4 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 72 log points at the 30th percentile of rainfall when insurance is marketed to laborers. This wage effect stays positive for the bottom 70 percentiles of rainfall experienced by our sample villages in 2011.

In Figure 5 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. Wages are higher with insurance in the good rainfall states. At the 80^{th} percentile of rainfall, wages increase by 19% and at median rainfall, insurance for both cultivators and agricultural laborers increase wages by 11.7%.

6. Concluding Comments

Comparing the graph with the combined insurance marketing (Figure 5) to the effects of marketing to the supply and demand sides in isolation (Figures 3 and 4) clarifies the value of combining general equilibrium analysis based on a model of the labor market with data generated by a randomized controlled trial. The net spillover effects of insurance marketing on wage volatility is virtually non-existent (Figure 5), 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 a framework for estimating general equilibrium effects of an important economic intervention: addressing a missing insurance market in an environment where the poor face large weather risk. The paper also illustrates how an RCT can be designed to capture aggregate effects. Our experimental design incorporated both individual-level and village-level variation in insurance marketing, and stratified the marketing by two occupational groups (landed cultivators and landless agricultural laborers) that represent the demand and supply sides of the agricultural labor market. This design helps to clearly identify labor demand and labor supply responses.

In the process, our research yields a clear and important policy message – the current practice of designing insurance contracts on the basis of 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 since 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	$1 - \gamma - \dfrac{\gamma(m+(1-p)I)}{w^L}$	$1 - \gamma - \dfrac{\gamma(m-pI)}{w^H}$
Uninsured labor supply	$1 - \gamma - \dfrac{\gamma(m)}{w^L}$	$1 - \gamma - \dfrac{\gamma(m)}{w^H}$
Difference insured and uninsured	$\dfrac{-\gamma(1-p)I}{w^L}$	$\dfrac{\gamma pI}{w^H}$

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

Table 3: Correlations between Sampling Eligibility Variables and Village and Caste Characteristics

Agricultural Labors	Fraction of Agri. Laborers eligible to receive insurance marketing	Fraction of agricultural labor households that received insurance marketing	Fraction of agricultural labor households that received insurance marketing	
			Conditional on: Fraction of laborers eligible to receive insurance marketing, state FEs	Conditional on: Fraction of laborers eligible to receive insurance marketing, state FEs and population share of laborers
Total # of households in village	0.125	-0.103	-0.138	-0.134
	(0.432)	(0.514)	(0.383)	(0.398)
Total # of castes in a village	0.058	-0.385	-0.207	-0.208
	(0.716)	(0.012)	(0.188)	(0.187)
Proportion of village accounted for by largest caste	-0.145	0.056	0.047	0.056
	(0.361)	(0.724)	(0.769)	(0.724)
Measure of concentration of castes 1-sum(proportion^2)	0.152	-0.033	-0.021	-0.029
	(0.336)	(0.837)	(0.896)	(0.856)

Cultivators	Fraction of Cultivators eligible to receive insurance marketing	Fraction of cultivator households that received insurance marketing	Fraction of cultivator households that received insurance marketing	
			Conditional on: Fraction of cultivators eligible to receive insurance marketing, state FEs	Conditional on: Fraction of cultivators eligible to receive insurance marketing, state FEs and population share of cultivators
Total # of households in village	0.163	-0.079	-0.153	-0.132
	(0.304)	(0.618)	(0.334)	(0.406)
Total # of castes in a village	-0.29	-0.352	-0.096	-0.077
	(0.062)	(0.022)	(0.545)	(0.630)
Proportion of village accounted for by largest caste	0.256	0.047	-0.138	-0.152
	(0.102)	(0.767)	(0.385)	(0.335)
Measure of concentration of castes 1-sum(proportion^2)	-0.291	-0.073	0.123	0.137
	(0.061)	(0.644)	(0.436)	(0.385)

P-values in parentheses.

Table 4: Sample Characteristics

	Mean	SD	N
Sample for Labor Demand Estimates	Cultivator Households, Acreage>.5		
Offered Insurance	0.620	0.485	1,585
Acreage Cultivated	2.56	4.15	1,584
Days of Harvest Labor	15.1	23.9	1,575
Days of Planting Labor	22.5	32.7	1,575
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 5: Village Fixed Effects Estimates: Demand for Kharif Season Labor by Cultivators by Stage of Production (Cultivators with at least .5 acres)

	(1)	(2)	(3)	(4)
VARIABLES	Days of Harvest Labor		Days of Planting Labor	
Offered Insurance in 2011	-0.161	-1.030	-1.669	-0.383
	(-0.12)	(-0.45)	(-1.49)	(-0.26)
Offered Insurance x Deviation of Kharif 2011 Rain per Day from Historical Average	0.654	0.835	0.459	0.191
	(2.39)	(1.96)	(1.41)	(0.48)
Offered Insurance in a Village where Payout Occurred		2.324		-3.442
		(0.70)		(-1.22)
Acreage Cultivated	2.462	2.460	2.994	2.997
	(2.43)	(2.43)	(2.56)	(2.56)
Observations	1,468	1,468	1,468	1,468

Robust t-statistics, based on standard errors clustered by village-caste, in parentheses

Table 6: Village Fixed Effects Estimates: Labor Supply and Migration 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	-2.559	-0.162	-323.1	-21.10
	(-3.14)	(-3.46)	(-1.83)	(-5.28)
Offered Insurance x Deviation of Kharif 2011 Rain per Day from Historical Average	-1.197	0.0155	-161.9	3.298
	(-3.05)	(1.30)	(-1.83)	(2.01)
Male	0.192	0.114	5.131	5.523
	(5.47)	(4.06)	(1.09)	(1.98)
Observations	515	2,932	287	1,191
Predicted Effect of Insurance Offer at Median Rainfall (t-stat)	-0.285	-0.0846	-15.44	-4.611
	(-3.051)	(-1.635)	(-1.391)	(-0.600)

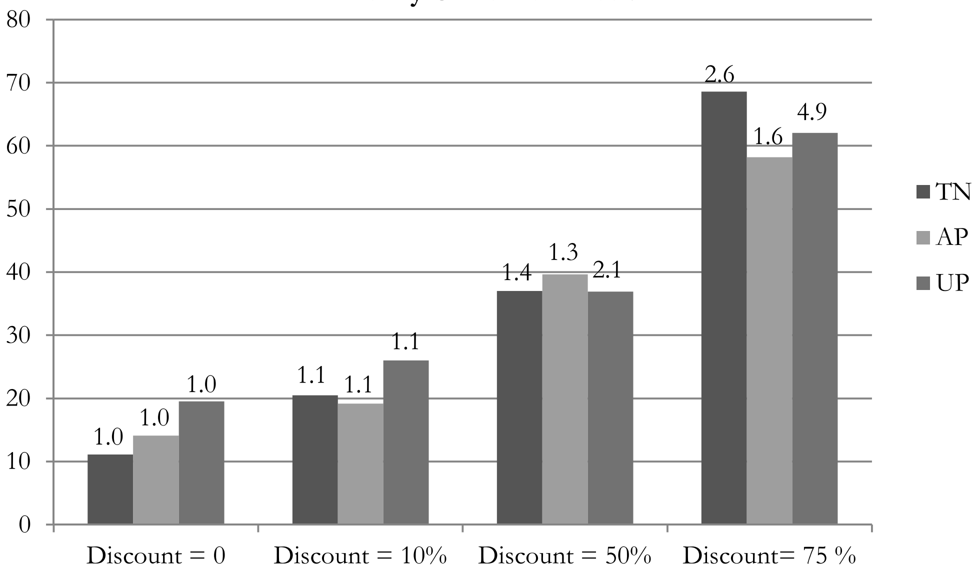
Robust t-statistics, based on standard errors clustered by village-caste, in parentheses. Age and age-squared also included as controls.

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.

Figure 1
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 2

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

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

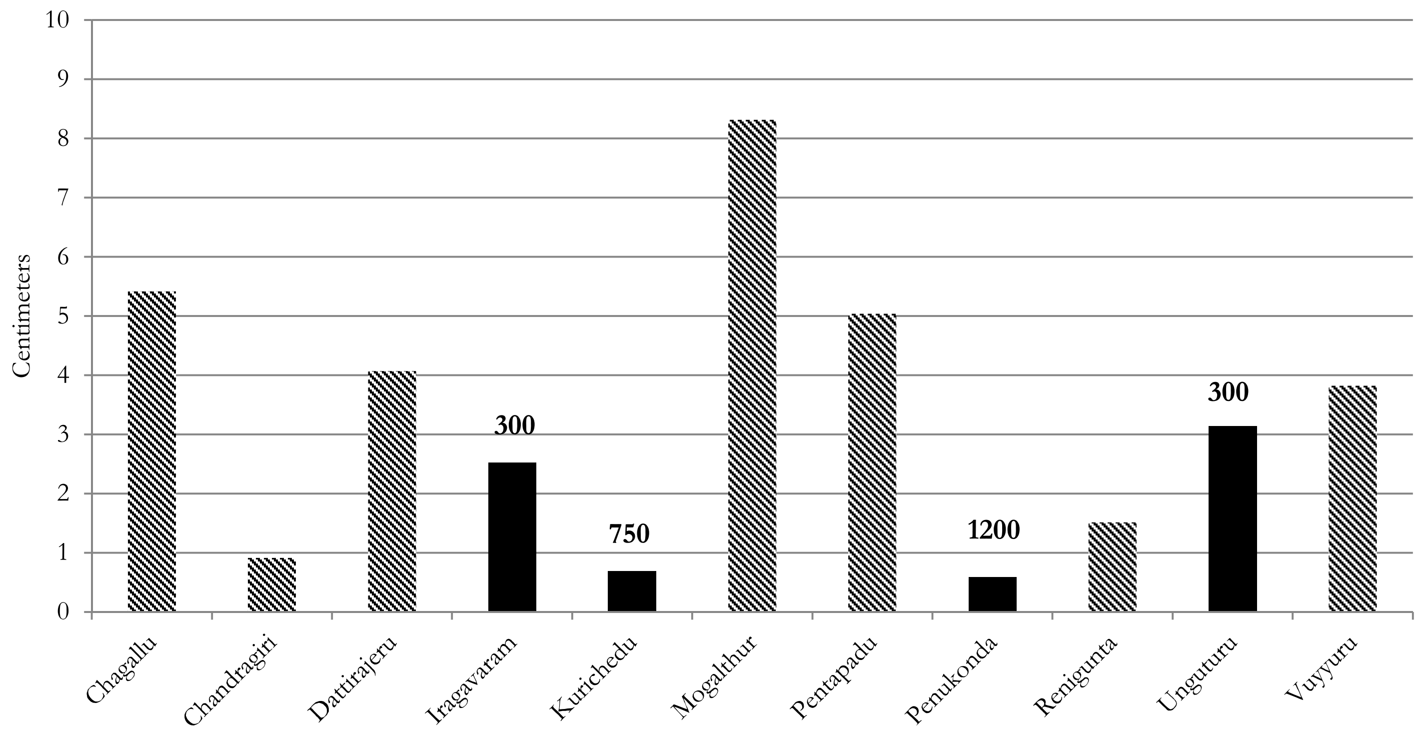
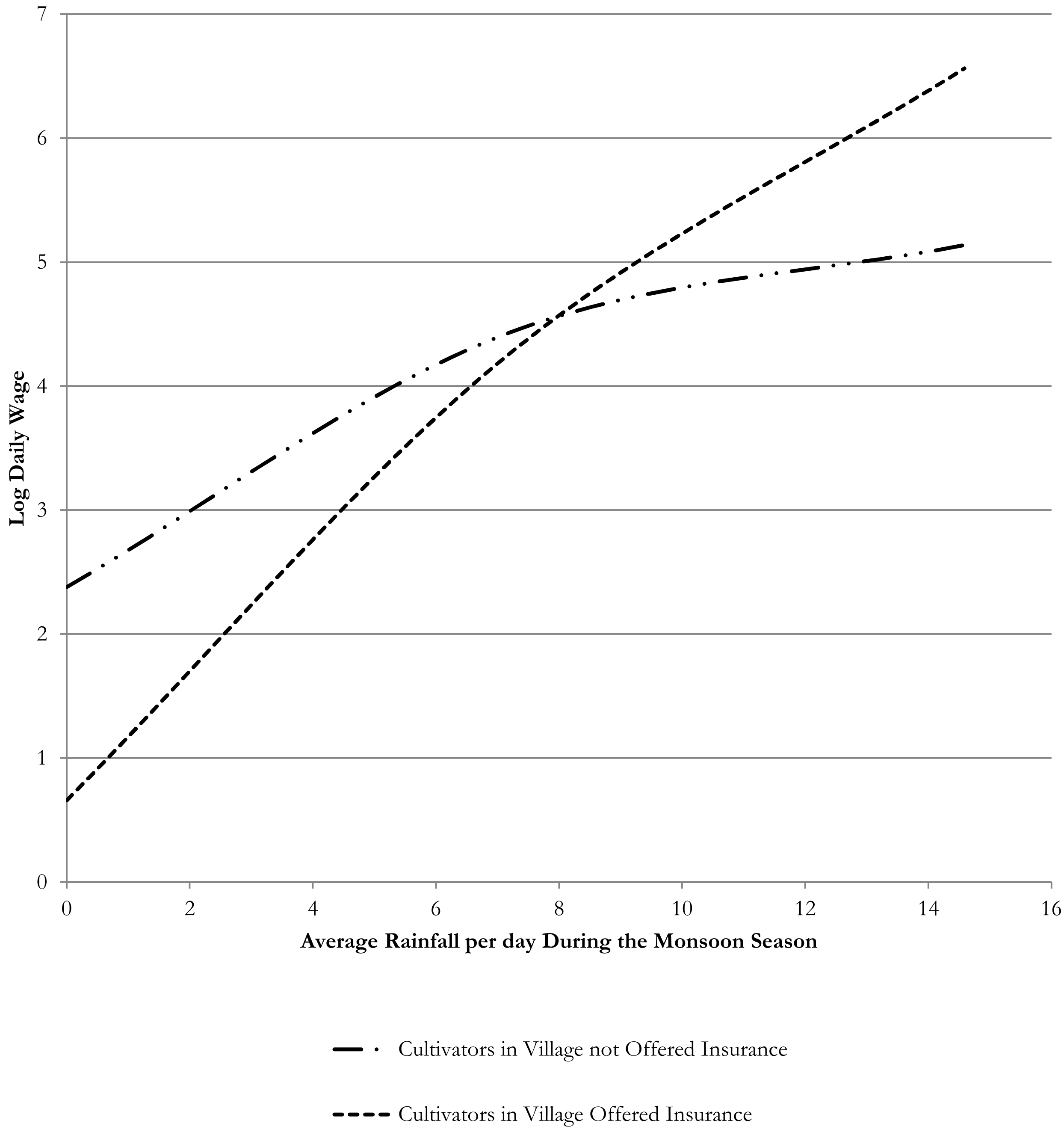
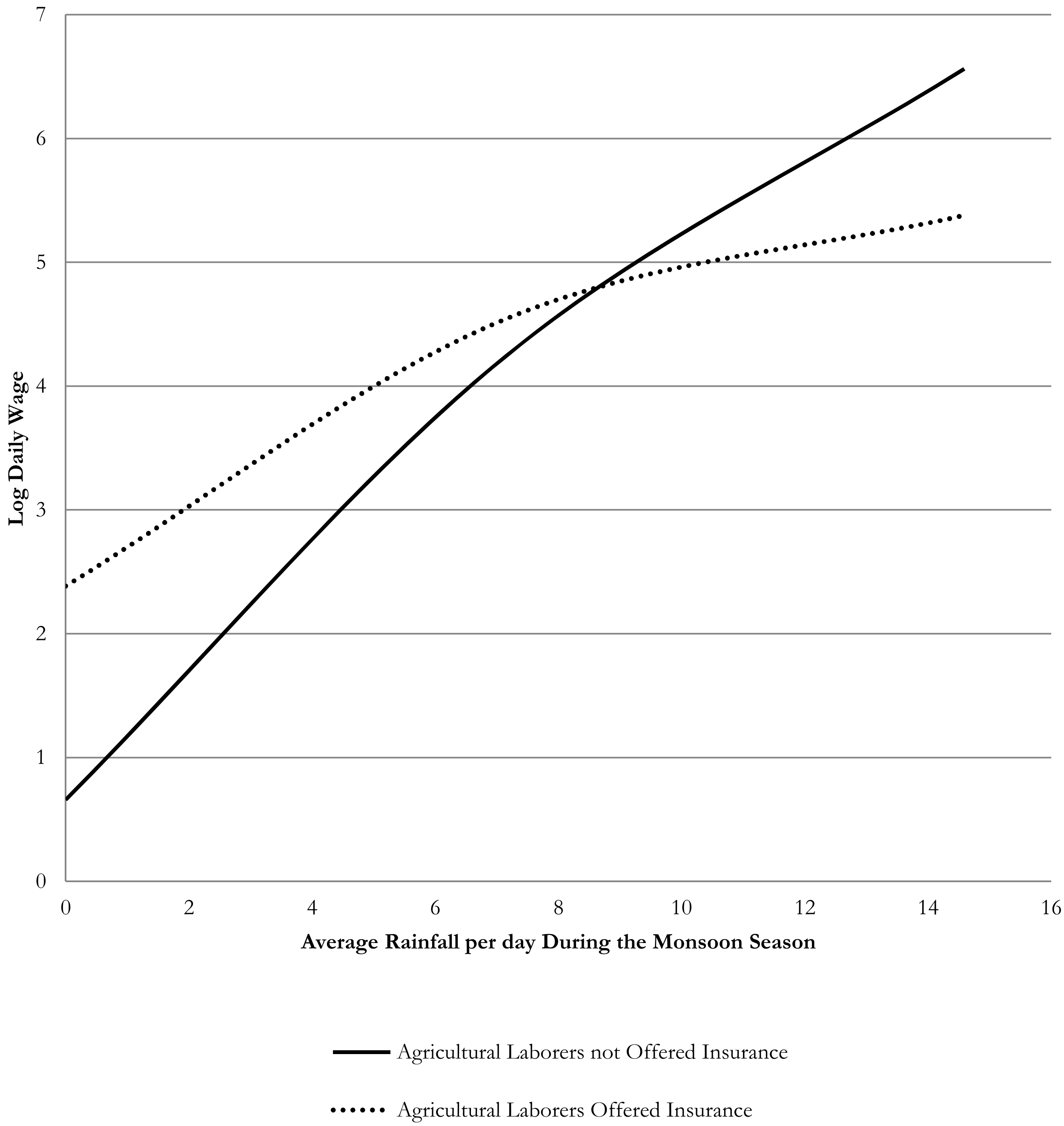


Figure 3: Effect of Marketing Rainfall Insurance to Cultivators on the Equilibrium Wage Rate



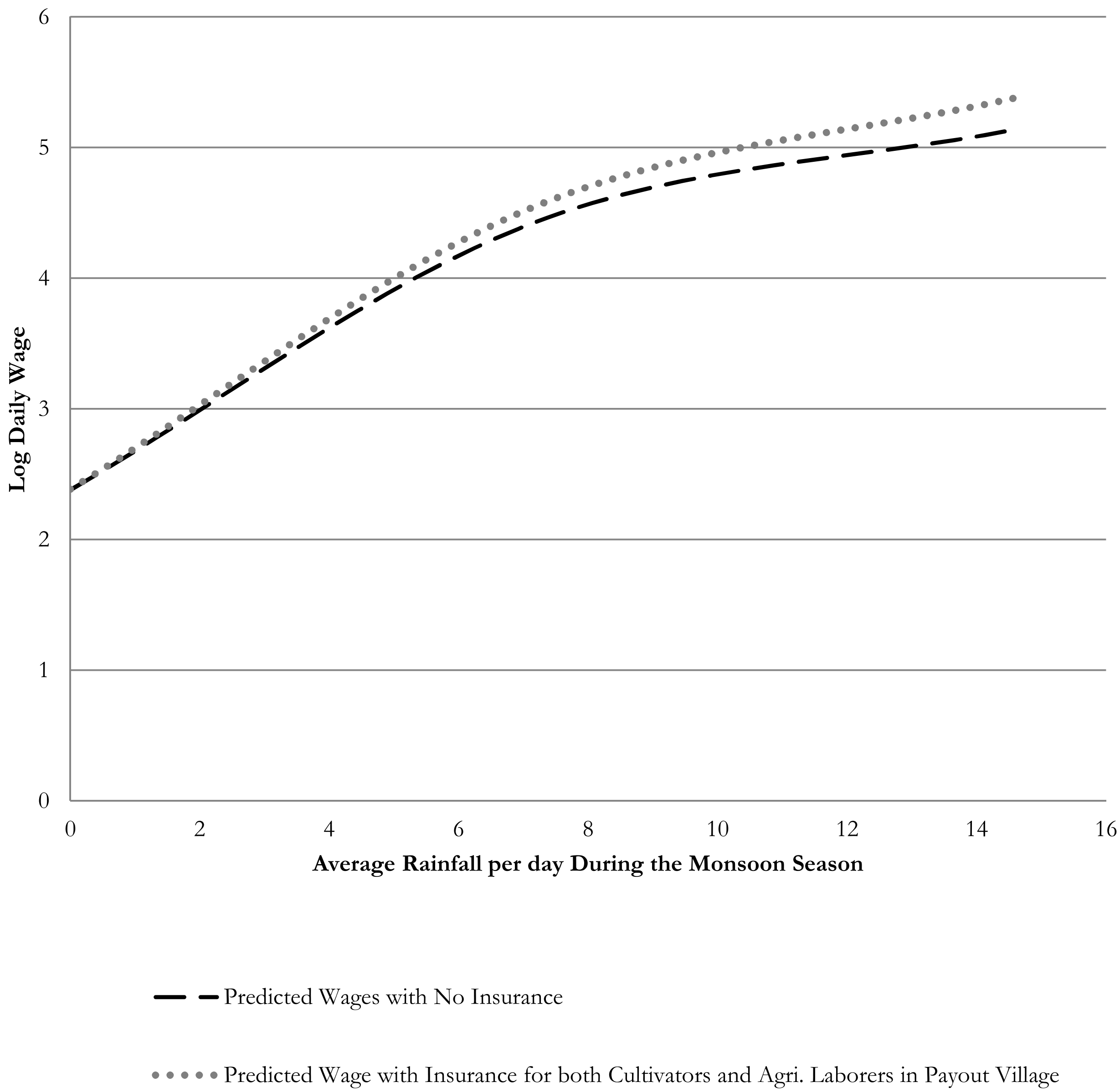
The wage rate is predicted based on the wage equation estimated in the second column of Table 7. Assumes an "average" village in terms of banks, roads, bus stops and fractions of cultivators and agricultural laborers in the populations, and that laborers do not receive insurance marketing. Graph is plotted for 2 standard deviations of rainfall per day around the mean.

Figure 4: 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 second column of Table 7. 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 5: 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 second column of Table 7. 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.