Title:

Weather Risk, Wages in Kind, and the Off-Farm Labor Supply of Agricultural Households in a Developing Country

Authors:

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Abstract:

This article investigates the effects of weather risk on the off-farm labor supply of agricultural households in a developing country, distinguishing different types of off-farm labor markets. A multivariate two-limit tobit model is applied to data from India. The regression results show that the share of the off-farm labor supply increases with weather risk, the increase is much larger in the case of non-agricultural work than in the case of agricultural wage work, and the increase is much larger in the case of agricultural wages paid in kind than in the cash wage case, suggesting farmers' considerations of food security.

Keywords:

covariate risk, food security, India, non-farm employment, self-employment.

Running head:

Weather Risk and Labor Supply of Farm Households

Leading unnumbered footnote:

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This article investigates the effects of weather risk on the off-farm labor supply of agricultural households in a developing country. In low-income developing countries like India, markets for agricultural inputs and outputs are well-developed, while the development of credit and insurance markets has been lagging behind (Townsend 1994; Kochar 1997a; 1997b). This means that people in general, and particularly poor farmers, have few means to hedge against the vagaries of production and price shocks that may put their livelihood at risk (Fafchamps 2003; Dercon 2005). It has long been argued that poor farmers in developing countries attempt to reduce their exposure to risk by growing their own necessities (Finkelshtain and Chalfant 1991; Fafchamps 1992; Kurosaki and Fafchamps 2002), diversifying their activities (Walker and Ryan 1990; Kurosaki 1995), adopting risk-reducing production inputs/factors (Just and Pope 1979), and through other income smoothing measures. If risk avoidance inhibits gains from specialization and prevents farmers from achieving the output potential they would be capable of, the provision of efficient insurance mechanisms becomes highly important in poverty reduction policies.

As an example of such inefficiency due to risk avoidance, we focus on the labor supply of farmers in developing countries. In the development literature, the relationship between risk and labor market participation has been analyzed by several authors. For example, Kochar (1999) and Cameron and Worswick (2003) examined the role of labor market participation as an *ex post* risk-coping mechanism for households hit by *idiosyncratic* shocks, such as injury or plot-level crop failure. The two studies showed that additional wage income was critically important for shock-hit households in India (Kochar) and in Indonesia (Cameron and Worswick) to maintain consumption levels. Rose

(2001) focused on the role of labor market participation both as an *ex ante* and an *ex post* response to *covariate* shocks. She showed that households facing a greater risk in terms of the reliability of rainfall were more likely to participate in the labor market (*ex ante* response). Moreover, unexpectedly bad weather and low rainfall also increased labor market participation (*ex post* response). Finally, Townsend (1994) showed that Indian villagers found it more difficult to insure against covariate risk than against idiosyncratic risk.

Taking these findings as our point of departure, we argue that in low-income developing countries, it is important to distinguish different types of off-farm labor markets: agriculture and non-agriculture on the one hand, and, wages paid in cash and wages paid in kind on the other. This article shows that the distinction matters in determining the off-farm labor supply of farmers in a developing country. The evidence shown in this article contributes to the existing literature on risk-poverty linkages in three ways.

First, the quantitative evidence on locally-covariate shocks on household behavior is still very scarce for developing countries in general. The classic paper on households' risk coping in India (Townsend 1994) suggested the difficulty to cope with locally-covariate shocks, but its main analysis was focused on the extent to which idiosyncratic shocks affect the welfare of the poor. The impact of locally-covariate shocks on household welfare has been discussed often in the Sub-Sahara African context (e.g., Fafchamps 2003), where the land-man endowment ratio is more favorable and rural markets are more segregated due to large transportation costs than in South Asia. Considering the concentration of the poor in South Asia, the quantitative evidence in this article is important in understanding risk-poverty linkages in developing countries. Rose's (2001) analysis for India simply considered a single labor market outside the farm, without considering the possible heterogeneity of off-farm labor returns. This article explicitly focuses on the difference between the covariance between farming returns and agricultural wages on the one hand, and the covariance between farming returns and non-agricultural wages on the other. When an area is hit by bad weather, this may lead to a decline not only in a farmer's own farm income but also reduce the demand for agricultural labor outside the farm, resulting in a high covariance between own-farm returns and wages available from agricultural work. In contrast, wages outside agriculture are likely to be less correlated with own-farm returns because they are less likely to be affected by the same kind of shocks. This line of reasoning suggests that agricultural households would find it more attractive to engage in non-agricultural work as a means of *ex ante* risk diversification.

The second point that distinguishes this article from the existing studies is our focus on in-kind wages[1] and our attempt to understand them based on explicit modeling of farmers' optimization under food price risk. In the literature on farmers' production choice, Finkelshtain and Chalfant (1991) and Fafchamps (1992) showed the theoretical possibility that farmers' crop choices are affected by the covariance between farm revenue and food prices, because growing crops whose returns are risky but positively correlated with food prices is advantageous to food-insecure farmers. Kurosaki and Fafchamps (2002) show that this effect is empirically significant in explaining poor farmers' cropping choice in Pakistan. Adjustments in production choices are not the only way to improve food security, however. Another possibility to achieve food security is through off-farm labor markets.

For farmers for whom food security is an issue, agricultural work may be more attractive than non-agricultural work if agricultural wages are paid in kind, since the monetary value of wages paid in paddy (the staple crop) is positively correlated with the paddy price. This line of reasoning suggests that food-insecure farm households would find it more attractive to engage in agricultural work paid in kind as a means of improving food security. Despite the importance of in-kind wages in developing countries, especially during the early stage of development, this aspect has been neglected in the literature. This article explicitly models this aspect, thereby providing a new insight to understand the functioning of rural labor markets.

Third, the empirical evidence of this article focuses on the impact of weather risk, which is closely related with an emerging literature on weather index insurance in developing countries.[2] In the existing literature on weather index insurance, the level of potential insurance demand has been analyzed extensively, but mostly based on a reduced-form approach. This article shows one mechanism of the risk-poverty linkages underlying such insurance demand. The econometric results show that distinguishing off-farm sectors into agricultural wage work paid in cash, agricultural wage work paid in kind, and non-agricultural wage work is important, suggesting that demand for weather index insurance may also vary depending on the characteristics of off-farm labor markets.

The remainder of the article is organized as follows. In the next section, we present a theoretical model to explain how farmers decide to allocate their labor, incorporating considerations of food security. We test the predictions of the model using household data from two Indian states, Bihar and Uttar Pradesh. The dataset is described in the third section, while the regression results of a multivariate two-limit tobit model of labor allocation are presented in the fourth section. The results robustly show that the share of the off-farm labor supply increases with weather risk, the increase is much larger in the case of non-agricultural work than in the case of agricultural wage work, and the increase is much larger in the case of agricultural wages paid in kind than in the cash wage case. The fifth section shows simulation results based on the regression estimates in order to examine whether the sectoral difference is economically significant. The last section concludes the article.

A Theoretical Model of Labor Allocation

In this section, we present a theoretical model to guide our empirical analysis of labor supply shares to different activities. Throughout the section, we assume a unitary decision making process at the household level with respect to labor allocation (Singh, Squire, and Strauss 1986).[3] To stylize the conditions of low-income developing countries, we assume that there are only three consumption goods: "leisure," which is defined as the residual after subtracting labor supply from the time endowment; "food," which is the main output in production and an important item in consumption; and "non-food," whose price is normalized at one. The food price is p (= $\theta_p \bar{p}$), where θ_p is the multiplicative price risk with a mean of one.

Time is divided into discrete intervals during which decisions are made and exogenous price and output shocks are realized. The timing of shocks and decisions is as follows. In period 1, the household decides on labor supply, enjoying leisure. After period 1, the household observes the realized prices and labor returns. Depending on the realization, the value of consumption expenditure y is determined. In period 2, the household allocates y into "food" and "non-food," enjoying consumption of the two goods.

Letting L denote the total labor supply, $u(L)$ denote the disutility from work in period 1 ($u'(L) < 0$, $u''(L) < 0$, which implies that the marginal disutility of labor increases with more labor), and $v(y, p)$ denote the indirect utility function derived from the second period optimization. We assume that the welfare of the household at the time of labor decision making[4] is measured by $u(L) + \mathrm{E}[v(y, p)]$, where E[.] is an expectation operator. We assume the following properties for $v(y, p)$:

$$v_y > 0, \quad v_p < 0, \quad v_{yy} < 0, \quad v_{pp} < 0, \quad v_{yp} > 0, \quad v_{yyy} > 0. \tag{1}$$

The first two properties are required for a valid indirect utility function. The third property guarantees that the household is risk-averse in the Arrow-Pratt sense, and the fourth implies that, for a given income level, the household's welfare decreases when the food price variability increases. The fourth property is especially appropriate for a (potentially) food-insecure household in a developing country (Kurosaki 2006). The last assumption, $v_{yyy}>0$, corresponds to "risk prudence," which is required for the welfare cost of consumption fluctuations to decrease with the level of expected consumption (Kimball 1990). In effect, these assumptions guarantee that the household behaves in a risk-averse and prudent way with respect to income variability, suffers if food price variability is higher, and gains if the correlation between the food price and income is higher.[5]

There are four different types of activity to which the household can allocate labor L (indicated by subscript j): own farming ($j = a$), agricultural wage work paid in cash ($j = b$), agricultural wage work paid in kind ($j = c$), and non-agricultural wage work ($j = d$). We assume that non-agricultural wages are always paid in cash, which is the simplification of the fact in India that in-kind wages are more prevalent in the agricultural labor market than in the non-agricultural labor market (Datta, Nugent and Tishler 2004). The decision variables are L and the shares of each type of labor (ℓ_j). From each activity, the household obtains a labor return of $\theta_j f_j(\ell_j L)$, where θ_j is the multiplicative risk at the local level with a mean of one, and $f(.)$ is a function characterizing the expected value of the labor return. Function $f(.)$ is likely to be linear for wage work outside the farm while it is likely to be concave for own farming. Thus, the household's optimization problem in period 1 is expressed as:

(2) $$\max_{\ell_j, L} \; u(L, X_p) + \mathrm{E}[v(y, p, X_p)],$$

subject to the budget constraint

(3) $$y = y_0 + \sum \theta_j f_j(\ell_j L, X_w),$$

the time constraint

(4) $$\sum \ell_j = 1, \quad L \le L_0,$$

where L_0 is the time endowment, and the non-negativity conditions for L and ℓ_j, $j = a, b, c, d$. X_p and X_w are vectors of household characteristics: X_p includes shifters of preferences such as those affecting risk aversion and food subsistence needs, while X_w includes shifters of household members' productivity, such as land, fixed capital, and human capital. y_0 denotes unearned income.

The first order conditions for the interior solution to this optimization problem are as follows:

(5) $$\mathrm{E}[v_y\theta_j]\frac{\partial f_j}{\partial L_j} = \mathrm{E}[v_y\theta_k]\frac{\partial f_k}{\partial L_k} \equiv W(v_y, \theta, X_p, X_w), \qquad j \ne k,$$

$$-u'(L, X_p) = \sum \ell_j \, \mathrm{E}[v_y \theta_j] \frac{\partial f_j}{\partial L_j} = W(v_y, \theta, X_p, X_w), \tag{6}$$

where $\partial f_j / \partial L_j = \partial f_j / \partial (\ell_j L)$, which is the expected value of the marginal labor return on activity j, and $W(.)/\mathrm{E}[v_y]$ is the shadow price of leisure for the household. When there is no risk, or there is risk but v_y and θ_j are independent for all j, equation (5) reduces to the familiar condition that marginal returns are equilibrated across activities and equation (6) reduces to the familiar condition that the labor-leisure choice equilibrates the marginal rate of substitution between consumption and leisure with the market wage rate. This is unlikely, however, when there is risk — we expect v_y and θ_j to be negatively correlated through the budget constraint (3) and due to the assumption of v_{yy} <0.

Applying the implicit function theorem to (5) and (6), we obtain the reduced-form optimal solution as

$$L^* = L(X_p, X_w, \Sigma), \qquad \ell^*_j = \ell_j(X_p, X_w, \Sigma), \qquad j = a, b, c, d, \tag{7}$$

where Σ is the covariance matrix of θ_a, θ_b, θ_c, θ_d, and θ_p. To stylize typical situations in rural India, the theoretical discussion assumes the following: (i) non-agricultural wages are not correlated with farm income, agricultural wages, and the food price; (ii) farm income and agricultural wages are positively correlated, and the correlation is greater when wages are paid in kind (i.e. food) than when wages are paid in cash; and (iii) agricultural wages and the food price are positively correlated, and the correlation is greater when wages are paid in kind than when wages are paid in cash. Under these assumptions, it is likely that the optimal labor choice satisfies the following relations:

$$(8) \qquad \frac{\partial \ell_a^*}{\partial \sigma_a} < 0, \qquad \frac{\partial \ell_c^*}{\partial \sigma_a} > \frac{\partial \ell_b^*}{\partial \sigma_a}, \qquad \frac{\partial \ell_d^*}{\partial \sigma_a} > \frac{\partial \ell_b^*}{\partial \sigma_a},$$

where σ_a is the coefficient of variation of θ_a (see Ito and Kurosaki 2008, Appendix I, for the derivation).

The first relation in (8) implies that the own-farm labor supply declines as production becomes riskier. In other words, farmers find it more attractive to engage in off-farm work as a means of *ex ante* diversification under riskier farming conditions. However, the alternatives to own-farm work are not homogeneous. The second and third relations in (8) imply that it is agricultural wage work paid in kind and non-agricultural wage work that absorb a larger share of the displaced labor. This is what we empirically test in the fourth section.

The reason why agricultural wage work paid in kind is more attractive to farmers than agricultural wage work paid in cash is as follows. When the food price fluctuates, what matters to farmers is not the level or stability of nominal income but the level and stability of real income. Since the food price and shocks to labor returns are not independent, the labor allocation may affect the level and stability of food-insecure farmers' real income through the covariance between the food price and shocks to labor returns (Fafchamps 1992). Since wage levels are usually rigid, the correlation is expected to be close to zero when the agricultural wage is paid in cash, while it is expected to be positive when the wage is paid in kind (Kurosaki 2006). As the second relation in (8) shows, agricultural work paid in kind is more attractive than agricultural work paid in cash because of the difference in the correlation. Thus, as an empirically verifiable prediction, we test whether the effect of σ_a on the labor supply share to agricultural wage work paid in kind is larger than that on the labor share to agricultural wage work paid in cash.[6]

Data

In the empirical part of this article, we use data obtained from the *Survey of Living Conditions, Uttar Pradesh and Bihar*, which is one of the Living Standard Measurement Study (LSMS) surveys conducted in developing countries with technical guidance from the World Bank. Uttar Pradesh (UP) and Bihar are located in the Ganges Plain of North India and are known for their high incidence of poverty. The survey was conducted in 1997/98 and covers 1,035 households from 57 villages in 13 districts of Bihar and 1,215 households from 63 villages in 12 districts of UP. To focus on the labor allocation of agricultural households, households operating no farmland and households with missing information on labor were excluded from our analysis (the number of excluded households is 580). The sample used in this article thus comprises owner farm households, owner-cum-tenant farm households, and pure tenant households.

Household Data on Labor Allocation

Information on working days per month and average working hours per day is available for each household member from January 1997 to December 1997. From this information, we compile the household-level data on the amount of labor allocated to each of the following five activities: (a) self-employment in agriculture, (b) wage work in agriculture paid in cash, (c) wage work in agriculture paid in kind, (d) wage work in non-agriculture, and (e) self-employment in non-agriculture. Based on these five activities, we divide patterns of labor allocation into 31 categories. In the upper portion of table 1, the top seven categories and the sum of the other 24 categories are shown first, followed by figures combining some of the 31 categories. Households relying only on self-employed work account for 41.4% of the total, while households that combine own farming with wage work account for 36.4%. Yet, off-farm labor is clearly important for agricultural households: 58.6% of households had one or more family members that were engaged in wage work in agriculture or non-agriculture (‘Including (b), (c), or (d)’ in the table). The table also shows that work in non-agriculture was more frequent than off-farm wage work in agriculture (48.3% versus 28.4% of households).

The lower portion of table 1 shows the household characteristics arranged by the three typical patterns of labor allocation. Comparing the second row titled ‘Self-employment only’ with the other rows, we see that farm households with income sources other than own farming have less farmland. For households with only small landholdings relative to the number of household members, it is difficult to make a living based on farming alone. Such households consequently allocate more labor to off-farm work. Similar findings have been reported for India as a whole based on nation-wide surveys in 1999/2000 (NSSO 2000) and 1993/94 data collected by the National Centre of Applied Economic Research (Lanjouw and Shariff 2004).

The column titled ‘Annual labor supply’ in table 1 also shows that households not engaged in wage work (‘Self-employment only’) supply the smallest amount of labor per household. By dividing ‘Annual labor supply’ by ‘No. of working members,’ we can obtain the total labor supply per person. The households not engaged in wage work still supply the smallest amount of labor per person. According to the standard agricultural household model (Singh, Squire, and Strauss 1986), the smaller labor supply of these farm households indicates that their reservation wage is higher than that of other households because these farm households have larger landholdings.

District Data on Rainfall and the Estimation of Covariate Risk

In order to empirically test the theoretical predictions, we need a proxy for σ_a (the coefficient of variation of local production shocks in farming). As the proxy variable, we compile the coefficient of variation of rainfall at the district level. The data source is Johnson et al. (2003), who provide grid-level monthly precipitation data distinguished by longitudes and latitudes. We calculate district-level rainfall data using four nearest neighbor grid points ([two nearest neighbor longitudes] times [two nearest neighbor latitudes]) and then take a weighted-average of them using the distance as weights. We employ monsoon rainfall (sum of monthly rainfalls from June to September) in the calculation of rainfall variables. To confirm that the variation of the rainfall variable thus calculated is a relevant proxy, we regress rice production on the rainfall variable and other explanatory variables. The source for our data on rice production is GOI (2001).

Table 2, column 1 reports the results of this regression. To control for differences in topology, land fertility, and other agro-ecological factors, district fixed effects are included. The effect of rainfall on rice production is positive and statistically significant at the 1% level: an increase in rainfall by one standard deviation raises rice production by 9,800 tons. Our rainfall variable is thus a good proxy for the rice production risk. In addition, rice production and the agricultural value-added at the state level are highly correlated, with a time-series correlation coefficient of 0.85 for Bihar and 0.97 for UP. Therefore, our rainfall variable is a valid proxy for the agricultural production risk at the district level.

In order to verify the validity of the assumptions (i) and (ii) in the theoretical model (non-agricultural wages are not correlated with farm income, while agricultural wages are positively correlated), we also regress daily wage rates of plowmen and carpenters on rainfall (table 2, columns 2 and 3). The data source on wage rates is GOI (1991-2000). After controlling for district heterogeneity by district fixed effects and controlling for fluctuation in prices by year dummies, the effect of rainfall on market wages is positive in both models, but only the effect on agricultural wages is statistically significant at the 5% level. In addition, the magnitude of the coefficient is larger than the magnitude of the coefficient in the non-agricultural wage regression. Therefore, our assumptions are validated by the data.

Description of Variables

Summary statistics of the variables used in the regression analysis are presented in table 3. The dependent variables are the shares of the different types of work: own farming ($j = a$), agricultural wage work paid in cash ($j = b$), agricultural wage work paid in kind ($j = c$), non-agricultural wage work ($j = d$), and own business in non-agriculture ($j = e$). Since the five shares add up to 100% by definition, we drop the last category, own business in non-agriculture, in the regression analysis below.

Adopting a reduced-form approach, we regress the four dependent variables on household characteristics (X) and a covariate risk factor (σ_a). In the theoretical discussion above, we distinguished between two types of household characteristics: those affecting households' preferences (X_p) and those affecting household members' productivity (X_w).

However, in the reduced-form approach, it is difficult to clearly assign each X either to X_p or to X_w. For instance, the size of a household's landholdings, credit status, the number of working-age household members, and their educational attainment may affect both the household's preferences and household members' productivity. Therefore, we do not attempt to clearly assign each of these variables either to X_p or to X_w but treat these variables as those controlling for X_p and X_w jointly. In addition to the landholding size, we include a dummy for land ownership. Since the landholding size variable captures the marginal effect of having an additional acre of land, the landholding dummy captures the threshold effect for a landless household to become a landowner. We can safely attribute part of this threshold effect to risk tolerance. We include the household-level irrigation ratio, mainly as a shifter of X_w, because irrigation enhances the average productivity on the farm and also stabilizes the farm output.[7] Since the price of irrigated land is higher than the price of unirrigated land, a portfolio impact through the difference in wealth may exist as well.

Controlling for X, we test the theoretical prediction with respect to σ_a. As covariate risk factors, ideally, we should include not only σ_a, but also the full covariance matrix of shocks to off-farm wages and food prices. Due to data constraints, this is left for future research. As a proxy for the coefficient of variation of production shocks, the district-level coefficient of variation of annual rainfall (*CV of rainfall*) is employed, using fifteen-year rainfall data at the district level (1985-1999) covering monsoon months from June to September. In addition, as another covariate risk factor, *Rainfall shock* is included to capture the *ex post* response of off-farm labor supply to production shocks. *Rainfall shock* variables were calculated as the deviation of rainfall in 1996 and 1997 (the year of the LSMS survey) from the fifteen-year average. We would expect a negative coefficient on this variable if households increase their off-farm labor supply primarily as a result of a failure in rainfall. On the other hand, if households increase their off-farm labor supply in anticipation of rainfall shocks, then we would expect a positive coefficient on the *CV of rainfall* variable.

As further control variables, we also include several village-level and district-level characteristics. These variables mainly control for differences in the availability of off-farm work, since households' allocations of labor to off-farm employment could be both supply and demand driven but our theoretical model focuses only on the supply side. Considering the existing studies using micro data from rural India on the determinants of off-farm employment opportunities (e.g., Lanjouw and Shariff 2004), we include a village-level irrigation indicator, average distance to the nearest bank, police, and secondary school, the level of infrastructure, the village-level wage levels, etc. These variables jointly control for the demand side factors regarding the availability of agricultural and non-agricultural off-farm employment opportunities. To avoid possible omitted variable bias, variables with insignificant coefficients are retained in the main specification when they are regarded as proxies for the determinants of labor allocation in the literature. After controlling for these effects, we can expect *CV of rainfall* to capture the precise impact of the covariate risk in agricultural production on labor supply.

Estimation Results

Using the dataset described above, we estimate the reduced-form determinants of off-farm labor supply. Since there are four dependent variables, all of which are truncated to the interval [0, 100], we employ a multivariate two-limit tobit model.[8] Estimation results are reported in table 4.

Among household characteristics, *Land owned*, *Irrigation ratio*, *Agric. capital*, and *Livestock* mostly have a positive effect on the on-farm labor supply (ℓ_a) and a negative effect on the off-farm supply (ℓ_b, ℓ_c, and ℓ_d). Since all of these variables raise the productivity of own farming, they mainly correspond to X_w (productivity shifters) in the theoretical model. In addition, in the context of rural India, these variables are also indicators of wealth, which may reduce households' risk aversion (Kurosaki and Fafchamps 2002). Thus, to some extent, these variables also correspond to X_p (preferences shifters) in the theoretical model.

Looking at education, we find that it significantly decreases the share of agricultural wage work. This reflects the lack of response of agricultural wages to human capital in South Asia (Kurosaki and Khan 2006) and the stigma associated in rural India with working as an agricultural laborer. Once villagers are educated, they tend to be very reluctant to perform manual agricultural work for others. Turning to the demographic variables, we find that the larger the number of working-age males and of dependents in a household, the lower is the labor share allocated to own farming and the higher share devoted to off-farm wage work. On the other hand, the number of working-age females in a household does not have a significant effect in all four equations. This result reflects the fact that adult women in rural India typically perform domestic chores. Looking at the role of castes, we find that households belonging to backward castes (*agric.-based backward* and *other backward*) or scheduled castes and tribes (*scheduled*) are more likely to send members to perform agricultural wage work. This result is consistent with Ito's (2009) finding of occupational segmentation or job discrimination against the backward castes using the same dataset.

Turning to the variable of interest in this article, *CV of rainfall*, we find that this has a significant negative impact on the on-farm labor supply (ℓ_a). Thus, the first theoretical prediction of (8) that the optimal on-farm labor supply is a decreasing function of farming risk is confirmed. This result implies that farm households facing riskier distributions of rainfall increase their off-farm labor supply. However, as shown in the table, the impact of weather risk varies widely across different types of off-farm work: while *CV of rainfall* has a significant positive impact on ℓ_c (agricultural work paid in kind) and ℓ_d (non-agricultural wage work), the impact of weather risk on ℓ_b (agricultural work paid in cash) is positive but statistically insignificant. In addition, the magnitude of the increase is much larger for ℓ_d than for ℓ_c. Thus, the second and third theoretical predictions of (8) that non-agricultural wage work absorbs a larger share of the displaced labor and the attractiveness of agricultural work increases when wages are paid in kind are confirmed. As predicted theoretically, agricultural households facing a greater weather risk tend to divert more labor to off-farm work, mainly in non-agriculture.

While *CV of rainfall* has the expected sign in all four equations and is mostly statistically significant, coefficients on *Rainfall shock* variables show a mixed result: Coefficients on *Rainfall shock in 1997* shows the expected pattern that good rainfall increases labor supply to own farm (ℓ_a) and decreases labor supply to off-farm, non-agricultural work (ℓ_d), although the first effect is not statistically significant; Coefficients on *Rainfall shock in 1996* shows the opposite sign, contrary to our expectation. *Rainfall shock in 1996* might have captured the effect of rainfall in the previous year on the current food prices, thereby affecting labor allocations, while *Rainfall shock in 1997* seems to have captured the supply response that drought-hit farmers increase labor supply to non-agricultural work.

To examine the robustness of our results, we try out various alternative specifications.[9] These additional results confirm that the share of the off-farm labor supply increases with weather risk, the increase is much larger in the case of non-agricultural work than in the case of agricultural wage work, and the increase is much larger in the case of agricultural wages paid in kind than in the cash wage case. On the other hand, the signs and statistical significance of coefficients on *Rainfall shock* variables were not very robust. Our results are thus slightly different from Rose's result (2001) that bad weather shocks significantly increase the off-farm labor supply. From these results, we conclude that our findings provide support for the hypothesis that off-farm labor is an *ex ante* income diversifying measure but show a mixed result for the hypothesis that it is an *ex post* measure.

A Simulation of the Impact of Weather Risk

In this section, simulation exercises are conducted based on the estimation results reported in table 4 in order to examine the economic significance of the effect of weather risk on off-farm labor supply. First, to compare our results with those of Rose (2001), the probability of wage labor market participation is simulated. Since the probability is not readily available from the multivariate tobit model adopted in this article, we employ the procedure outlined by Cornick, Cox, and Gould (1994) and run Monte-Carlo simulations.[10]

Table 5 reports our simulation results. Despite the difference in methodology and data, our simulation results with respect to off-farm work (agricultural wage work paid in cash, agricultural wage work paid in kind, and non-agricultural wage work pooled; last column) are qualitatively similar to those obtained by Rose (2001).[11] Our results indicate that, when the weather risk increases (*CV of rainfall* increases from its minimum to its maximum), the percentage of households participating in off-farm wage work increases from 46% to 84%. Both figures are larger than those obtained by Rose (2001), but the direction of change is the same. However, our research approach allows us to go further and decompose this response into three types of wage work. Doing so indicates that agricultural work paid in cash decreases by 3 percentage points, while agricultural work paid in kind increases by 21 percentage points and non-agricultural work increases by as much as 46 percentage points. The impact of weather risk on off-farm labor participation is thus very different across sectors.

In the lower half of table 5, we report simulation results of the expected changes in labor supply shares. The first two rows provide the response of ℓ_j. These figures show that the labor share allocated to off-farm work increases with the increase in *CV of rainfall* and the response of non-agricultural wage work is more substantial.

These results thus confirm that off-farm work in various sectors plays an important role in diversifying farm production risk. It is implied, therefore, that empirical and theoretical studies on farmers' labor supply response to risk should distinguish between different types of off-farm work involved. This implication is also confirmed by the results of further specification tests reported in table 6. We test the following null hypotheses: (1) all coefficients in the regressions for agricultural wage work (ℓ_b and ℓ_c) are equal and (2) all coefficients in the regressions for all three wage work (ℓ_b, ℓ_c, and ℓ_d) are equal. The LR χ^2 statistics show that both hypotheses are rejected at the 1 % level, indicating that the sectoral difference is substantial.

Conclusion

This article investigated the effects of weather risk on the off-farm labor supply of agricultural households in a developing country, distinguishing different types of off-farm labor markets: agriculture and non-agriculture on the one hand, and, wages paid in cash and wages paid in kind on the other. We developed a theoretical model of household optimization, which predicts that when farmers are faced with more production risk in their farm production, they find it more attractive to engage in non-agricultural work as a means of risk diversification, but the agricultural wage sector becomes more attractive when food security is an important issue for the farmers and agricultural wages are paid in kind. This prediction was confirmed by regression analyses using household data from rural areas of Bihar and Uttar Pradesh, India. Simulation results based on the regression estimates showed that the sectoral difference is substantial.

These results imply that risk avoidance inhibits gains from specialization and prevents farmers from achieving their output potential. Therefore, a crucial measure to reduce poverty in the study region would be to provide more efficient insurance or risk-reducing mechanisms. Such measures could take various forms: reducing variability in agricultural production and in food price by promoting risk-reducing technologies such as irrigation and/or food market integration, reducing the transmission of production shocks to income shocks through crop insurance schemes, improving credit opportunities to smooth consumption in the face of income shocks, etc. This study shows that labor markets potentially also play a role in reducing households' vulnerability to risk. If labor markets are used as an income diversifying measure, it is critically important to promote sectors whose wages are less correlated with farm production shocks. This is the main lesson of this article.

Considering the considerable diversity of earning opportunities in developing countries, a possible extension of our research on off-farm labor as a means of diversifying risk would be to disaggregate non-agricultural wage labor opportunities or to allow for endogenous on-farm diversification such as contract farming and farm product diversification. Since the regression model in this article included only the variance term of the shock to own farming, incorporating a full set of correlation coefficients among the shocks to different sectors would be an interesting exercise. These issues are left for further research using a dataset with additional variables.

[1] One aspect that has been analyzed in the existing literature regarding in-kind transactions is their impact on incentives and screening when a welfare scheme is implemented (see Chambers 1989 and Currie and Gahvari 2008). This article complements this line of research by showing a completely different function of in-kind transactions.

[2] See for example Gine, Townsend, and Vickery (2007) and companion papers published in the same issue of *American Journal of Agricultural Economics*.

[3] This assumption is based on our preliminary result from various demographic and health surveys in the world that bargaining issues are less important in South Asia than in Sub-Saharan Africa. Extending the analysis of this article under a non-unitary household modeling framework and empirically testing whether bargaining among members within a household is important in the current dataset are left for further study.

[4] See Fafchamps (1993) for a more flexible form of the labor-leisure choice under risk.

[5] Note that when the food price and nominal income are positively correlated, real income is more stable.

[6] The relations in (8) are based on several assumptions already described. The assumptions of income risk aversion v_{yy} <0 and food price risk aversion v_{pp} <0 are critically important. Without them, (8) do not hold and ℓ_a^* should not respond to σ_a. In the empirical test, however, we may observe relations similar to (8) in spite of risk neutrality, if several variables that directly affect labor supply shares (such as shifters of wage levels) are omitted and they are correlated with σ_a. Therefore, in the empirical analysis, we control for these variables as much as possible using various kinds of household-, village-, and district-level variables. Another critical assumption is our treatment of non-agricultural wage work as a homogeneous activity, remunerated through a single payment vehicle. Ignoring the possibility of non-agricultural wage work paid in kind and assuming no correlation between its wage and farm-related activities are a rough approximation of the situations in India. Relaxing these assumptions complicates the model but does not change the basic relations. The existence of competing non-agricultural wage work opportunities is ignored because in the equilibrium under the adopted assumptions, only the non-agricultural activity with the highest expected return per labor is chosen by the household.

[7] One may wonder why rainfall affects farm output when the average irrigation ratio is 80% (table 3). This is because the quality of irrigation is so low that farmers have to rely on rainfall as the main source of water required for crops. The irrigation quality is low in the study area because public canals are poorly maintained, resulting in frequent supply disruption, and private tubewells are subject to frequent electricity breakdowns.

[8] We wrote a STATA program for the maximum likelihood estimator using the Geweke-Hajivassiliou-Keane Simulator (GHKS) to estimate the tobit model. The program is available on request. Since the dependent variables are shares, the estimation can be implemented using a generalized linear model (GLM). However, in the context of this article, GLMs are not very appropriate for the following reasons. First, in general, GLMs

cannot address the correlation between unobserved factors (estimation errors) in a system of equations. Our results show that the null hypothesis of no correlation between errors is statistically rejected. Second, and the most important, the dependent variables in our model, labor supply shares, contain many zero values. Since a tobit type specification is most widely used for a model with corner solutions (Wales and Woodland 1983; Cornick, Cox, and Gould 1994; Perali and Chavas 2000; Kao, Lee, and Pitt 2001; Yen, Lin, and Smallwood 2003), we believe that a multivariate tobit model is the most appropriate one. In the literature, several authors have proposed alternative estimation approaches using Kuhn-Tucker conditions directly to deal with the corner solution problem (Wales and Woodland 1983; Lee and Pitt 1986). Comparing the results reported in this article with those estimated under these approaches is left for further research. Regarding the simulator to estimate the multivariate tobit model, we also considered other simulation methods such as the Gibbs Sampler Simulator (GSS). Balancing reliability and the computational ease, we adopted GHKS.

[9] We first re-estimate the same model under alternative specification with no adjustment for the possible correlation between errors. Then we examine the robustness with respect to the specification of the rainfall variables. See Ito and Kurosaki (2008) for the summary of the estimation results under these specifications.

[10] See Ito and Kurosaki (2008), Appendix III, for the simulation procedure. The computer program for the simulation is also available on request.

[11] Rose (2001) estimated a random effects probit model using a dummy variable for wage work participation as the dependent variable. Thus, her estimation results readily provide the figures for table 5 without the need for Monte-Carlo simulations. In addition, she used three-year panel data of 2,115 households spanning 13 states of India in 1968/69 - 1970/71.

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Table 1. Labor Allocation Patterns in Bihar and Uttar Pradesh, India

I. Labor allocation patterns[1]					
Pattern	No.	Freq.	Pattern	No.	Freq.
31 possible patterns:			Combining some of them:		
(a) only	353	21.1%	Self-employment only	691	41.4%
(a) and (d)	332	19.9%	Self-emp. agric & wage work	608	36.4%
(a) and (e)	322	19.3%	Including (a)	1,520	91.0%
(a), (d), and (e)	123	7.4%	Including (b) or (c)	474	28.4%
(a), (b), (c), and (d)	103	6.2%	Including (d)	806	48.3%
(a), (c), and (d)	52	3.1%	Including (b), (c), or (d)	979	58.6%
(a), (b), and (c)	45	2.7%			
Other 24 patterns	340	20.4%	Grand total	1,670	100.0%

II. Household Characteristics by Labor Allocation Pattern				
Pattern:	No. of obs.	Annual labor supply[2] (hours)	No. of working members[2]	Size of farmland owned (acres)
Total	1,670	3,240.7	2.43	2.71
Self-employment only	691	2,623.8	2.09	3.74
Including (b) or (c)	474	3,503.2	2.71	1.23
Including (d)	806	3,851.9	2.74	2.17

Notes: (1) (a) = Self-employment in agriculture; (b) = Cash payment wage work in agriculture; (c) = In-kind payment wage work in agriculture; (d) = Wage work in non-agriculture; (e) = Self-employment in non-agriculture.

(2) 'Annual labor supply' is the sum of hours working on own farm, hours supplied to wage work outside, and hours working on own non-farm enterprise. Reported figures are the averages for all households.

Table 2. The Effects of Rainfall on Rice Production and Market Wages

	Rice production		Agric. wages		Non-agric. wages	
Land under paddy	61.92	(9.65)***	—		—	
Rainfall	9.76	(3.00)***	2.93	(2.13)**	1.85	(1.02)
Intercept	172.25	(70.23)***	18.23	(8.78)***	38.07	(13.87)***
No. ob obs.	199		95		96	
R^2	0.78		0.60		0.54	

Notes: (1) The units of dependent variables are 1,000 metric tons (rice production), and rupees (market wages). Agricultural and non-agricultural wages are the annual average daily wages paid for plowmen and carpenters, respectively.
(2) Explanatory variables are standardized by subtracting their means and divided by their standard deviations.
(3) Coefficients on the standardized explanatory variables are reported and numbers in parentheses are t-values. Double asterisk (**) and triple asterisk (***) denote that the coefficient is statistically significant at the 5% and 1% levels, respectively.
(4) District fixed effects are included in all three specifications. In the regressions of market wages, year dummies (the reference period is 1990) are included in order to control fluctuation in prices.

Table 3. Summary Statistics of Regression Variables

Variable	Unit	Mean	Std. Dev.	Min.	Max.
Dependent variables: Labor hour shares (ℓ_j)					
(a) Self-emp., agriculture	%	44.43	36.21	0	100
(b) Wage work, agric. (cash)	%	5.59	15.60	0	100
(c) Wage work, agric. (in-kind)	%	6.74	16.77	0	100
(d) Wage work, non-agric.	%	25.50	32.38	0	100
(e) Self-emp., non-agric.	%	17.75	28.98	0	100
Explanatory variables: Household characteristics (X)					
Land owned(1)	acre	2.71	4.76	0	93
Irrigation ratio(1)	%	80.00	32.74	0	100
Agric. Capital	Rs.	7367.34	31149.75	0	373600
Livestock	Rs.	7228.88	9707.77	0	150000
Education(2)	year	3.51	3.59	0	18.5
Working-age males	person	1.89	1.17	0	8
Working-age females	person	1.71	1.06	0	7
Non-working-age members	person	3.06	2.17	0	17
Dummy for land owner(1)	—	0.95			
Caste dummies ('Upper' as the reference category)					
Middle	—	0.02			
Agric.-based backward	—	0.32			
Other backward	—	0.18			
Scheduled	—	0.22			
Muslim upper	—	0.04			
Muslim backward	—	0.04			
Explanatory variables: Covariate risk factors (σ_a)					
Rainfall shock in 1996(3)	mm	0.25	144.26	-250.81	236.84
Rainfall shock in 1997(3)	mm	-133.86	80.91	-249.18	25.19
CV of rainfall(3)	—	0.35	0.08	0.22	0.50
Explanatory variables: Village characteristics					
Irrigation indicator(4)	-	3.80	1.19	1	5
Distance to facilities	km	5.97	3.61	0.5	20
Ratio of landless	%	38.77	21.19	0	99
Road indicator(4)	—	2.75	0.99	1	4
Electricity dummy	—	0.54			
Agric. wage	Rs.	24.62	7.31	7	40
Non-agric. wage	Rs.	64.68	13.90	20	99
flood proneness(4)	—	1.98	1.16	1	5

Notes: (1) The sample is farm households, including pure tenant farmers who do not own land. *Land owned* is the size of farmland owned by the household. *Dummy for land owner* is based on *Land owned*. *Irrigation ratio* is the size of irrigated land owned by the household divided by *Land owned*. (2) *Education* is the average number of schooling years among working-age (aged 15-60) adults. (3) The coefficient of variation (*CV of rainfall*) was calculated based on fifteen-year rainfall data at district-level (1985-1999). *Rainfall shock* variables were calculated as the deviation of rainfall in 1996 and 1997 (the year of the LSMS survey) from the fifteen-year average. (4) *Irrigation indicator* and *Flood proneness* are village-level indicator variables with regard to irrigated farmland and flood-prone farmland (the proportion of total farmland in the village), taking 1 (0%), 2 (1-25%), 3 (26-50%), 4 (51-75%), 5 (above). *Road indicator* is an indicator variable with regard to the main road in the village, taking 1 (trail), 2 (dirt road), 3 (paved road), 4 (tar-paved road).

Table 4. Determinants of Labor Supply

	(a) Self-emp. agriculture		(b) Wage work, agriculture (cash payment)		(c) Wage work, agriculture (in-kind payment)		(d) Wage work, non-agriculture	
Household characteristics (X)								
Land owned	2.32	(2.14)**	-3.00	(2.38)**	-5.79	(4.20)***	-2.16	(2.03)**
Irrigation ratio	0.10	(1.60)	-0.18	(3.30)***	-0.02	(0.34)	0.03	(0.34)
Agric. capital $\times 10^{-4}$	-0.22	(0.38)	-4.85	(1.55)	0.71	(0.50)	-2.19	(2.42)**
Livestock $\times 10^{-4}$	4.96	(1.73)*	-3.14	(1.03)	-3.47	(1.56)	-6.44	(2.47)**
Education	-0.24	(0.40)	-2.13	(3.42)***	-2.45	(3.00)***	0.79	(1.19)
Working-age males	-5.82	(4.37)***	-3.07	(1.71)*	-1.90	(1.03)	11.03	(5.42)***
Working-age females	-0.23	(0.12)	3.08	(1.40)	0.25	(0.16)	2.18	(1.15)
Non-working-age members	-1.97	(2.89)***	1.62	(3.20)***	1.44	(1.92)*	1.14	(1.17)
Dummy for land owner	7.33	(1.15)	-7.29	(0.99)	-18.12	(2.28)**	-0.52	(0.05)
Caste dummies								
Middle	-14.79	(1.91)*	6.83	(0.43)	19.55	(1.04)	-12.78	(0.87)
Agri.-based backward	1.97	(0.40)	15.08	(2.39)**	29.78	(2.94)***	-5.84	(0.74)
Other backward	-16.41	(3.48)***	14.96	(1.92)*	40.58	(4.11)***	5.78	(0.70)
Scheduled	-23.56	(4.41)***	39.04	(5.94)***	65.24	(6.10)***	7.34	(0.96)
Muslim upper	-15.10	(1.82)*	10.29	(0.81)	24.55	(1.87)*	11.52	(0.83)
Muslim backward	-25.20	(4.45)***	0.72	(0.09)	15.29	(1.42)	-5.19	(0.47)
Aggregate risk factors (σ_a)								
Rainfall shock in 1996 $\times 10^{-1}$	-2.50	(2.72)***	-0.41	(0.49)	0.48	(0.56)	3.54	(4.02)***
Rainfall shock in 1997 $\times 10^{-1}$	1.04	(1.36)	1.27	(1.86)*	-0.24	(0.39)	-1.92	(2.55)**
CV of rainfall $\times 10^{2}$	-2.55	(2.74)***	0.19	(0.19)	1.40	(1.70)*	2.32	(2.35)**
Other controls								
Irrigation indicator	-0.73	(0.49)	2.12	(0.86)	2.28	(1.10)	-0.67	(0.29)
Distance to facilities $\times 10^{-1}$	-0.43	(0.81)	1.22	(1.92)*	-0.46	(0.69)	-0.29	(0.43)
Ratio of landless	-0.13	(1.49)	0.30	(2.59)***	0.25	(2.36)**	-0.10	(0.98)
Road indicator	-1.40	(0.91)	1.98	(0.79)	-4.17	(2.08)**	1.40	(0.54)
Electricity dummy	-2.95	(1.35)	-2.83	(0.52)	-1.67	(0.40)	-7.83	(1.28)
Agric. wage	-0.10	(0.38)	0.03	(0.09)	-0.49	(1.34)	0.23	(0.58)
Non-agric. wage	-0.28	(1.57)	0.29	(1.59)	0.24	(1.74)*	0.61	(2.75)***
Flood proneness	0.07	(0.06)	-0.52	(0.24)	0.92	(0.74)	1.91	(1.03)
Intercept	222.67	(3.17)***	-70.14	(0.77)	-129.78	(1.88)*	-221.52	(2.82)***
sigma	43.60	(23.87)***	45.19	(10.29)***	42.49	(9.64)***	60.17	(17.15)***
correlation	1.00		-0.38	(8.92)***	-0.52	(9.48)***	-0.66	(31.83)***
			1.00		0.40	(6.98)***	0.04	(0.96)
					1.00		0.18	(3.02)***
							1.00	

Notes: (1) Estimated using a multivariate two-limit tobit model (the lower limit is 0 and the upper limit is 100) with Geweke-Hajivassiliou-Keane (GHK) simulator (No. of draws = 50).

(2) Additional regressors include district characteristics, such as average rainfall in dry/rainy seasons, population, density, and literacy rate, and UP state dummy. Coefficient estimates on these variables have been dropped for brevity but are available on request.

(3) Numbers in parentheses are z-values based on clustering robust standard errors using districts as clusters. Single asterisk (*), double asterisk (**), and triple asterisk (***) denote that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

(4) No. of obs. = 1670; Log-likelihood = −15229.483.

(5) H_0: no correlation between errors; $LR\ \chi^2(6) = 936.524$ (P-value = 0.00).

Table 5. Labor Supply Simulation

A. Simulation of Wage-Labor Market Participation				
	(b) Wage work, agriculture (cash payment)	(c) Wage work, agriculture (in-kind payment)	(d) Wage work, non-agriculture	Wage work, any type
	$\Pr(\ell_b > 0)$	$\Pr(\ell_c > 0)$	$\Pr(\ell_d > 0)$	$\Pr(\ell_b + \ell_c + \ell_d > 0)$
		This paper		
CV of rainfall = 0.22(Min.)	0.18	0.12	0.28	0.46
CV of rainfall = 0.50(Max.)	0.21	0.33	0.74	0.84
Sample mean	0.21	0.15	0.52	0.59
		Rose (2001), Table3		
CV of rainfall = 0.16(Min.)	—	—	—	0.32
CV of rainfall = 0.91(Max.)	—	—	—	0.51
Sample mean	—	—	—	0.38

B. Simulation of Labor Supply Shares				
	(a) Self-emp. Agriculture	(b) Wage work, agriculture (cash payment)	(c) Wage work, agriculture (in-kind payment)	(d) Wage work, non-agriculture
	$E(\ell_a)$	$E(\ell_b)$	$E(\ell_c)$	$E(\ell_d)$
CV of rainfall = 0.22(Min.)	65.62	5.66	4.57	9.44
CV of rainfall = 0.50(Max.)	29.88	6.76	13.18	39.84
Sample mean	44.43	5.59	6.74	25.50

Note: $\Pr(\ell_j > 0) = \Pr(0 < \ell_j < 100) + \Pr(\ell_j = 100)$ and $E(\ell_j) = \Pr(0 < \ell_j < 100) \times E(\ell_j \mid 0 < \ell_j < 100) + 100 \times \Pr(\ell_j = 100)$. See Ito and Kurosaki (2008), Appendix III, for the simulation procedure.

Table 6. Specification Tests for the Labor Supply Model

	(a) Self-emp. Agriculture	(b) Wage work, agriculture (cash payment)	(c) Wage work, agriculture (in-kind payment)	(d) Wage work, non-agriculture
Without any restriction (table 4)				
CV of rainfall $\times 10^2$	-2.55 (2.74)***	0.19 (0.19)	1.40 (1.70)*	2.32 (2.35)**
Log-likelihood = -15229.48.				
With a restriction that all coefficients in equations (b) and (c) are equal.				
CV of rainfall $\times 10^2$	-2.54 (2.73)***	0.94 (1.31)		2.26 (2.30)**
Log-likelihood = -15255.92.				
H_0: the restricted model is true; $LR\ \chi^2(32) = 52.88$ (P-value = 0.01).				
With a restriction that all coefficients in equations (b), (c) and (d) are equal.				
CV of rainfall $\times 10^2$	-2.36 (2.87)***		1.42 (2.56)**	
Log-likelihood = -15386.30.				
H_0: the restricted model is true; $LR\ \chi^2(64) = 622.89$ (P-value = 0.00).				
With a restriction that all off-diagonal elements of the correlation matrix are zero.				
CV of rainfall $\times 10^2$	-2.69 (2.85)***	0.45 (0.45)	1.48 (1.71)*	2.02 (1.91)*
Log-likelihood = -15698.54.				
H_0: the restricted model is true; $LR\ \chi^2(6) = 983.12$ (P-value = 0.00).				

Notes: (1) Estimated using a multivariate two-limit tobit model (the lower limit is 0 and the upper limit is 100) with Geweke-Hajivassiliou-Keane simulator (No. of draws = 50).

(2) All regressions are implemented with other variables included, such as household, village, and district characteristics. Coefficient estimates on these variables have been dropped for brevity but are available on request.

(3) Numbers in parentheses are z-values based on clustering robust standard errors using districts as clusters. Single asterisk (*), double asterisk (**), and triple asterisk (***) denote that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.