Weather Risk and the Off-Farm Labor Supply of Agricultural Households in India

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Abstract

As one of the measures to smooth income, this paper focuses on the diversification of labor allocation across activities. A key feature of this paper is that it pays particular attention to differences in the covariance between weather risk and agricultural wages and between weather risk and non-agricultural wages. We estimate a multivariate tobit model of labor allocation using household data from rural areas of Bihar and Uttar Pradesh, India. The regression results show that the share of the off-farm labor supply increases with the weather risk, and the increase is much larger in the case of non-agricultural wage work than in the case of agricultural wage work. Simulation results based on the regression estimates show that the sectoral difference is substantial, implying that empirical and theoretical studies on farmers' labor supply response to risk should distinguish between the types of off-farm work involved.

JEL classification codes: Q12, O15, J22.
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1. Introduction

This paper investigates the effects of weather risk on the off-farm labor supply of agricultural households in two Indian states, Bihar and Uttar Pradesh. Despite the prevalence of poverty, markets for agricultural inputs and outputs are well-developed in these two states. The development of credit and insurance markets, however, has been lagging behind (Townsend, 1994; Kochar, 1997). This means that people in general, and particularly farmers, have few means to hedge against the vagaries of production and price shocks that may put their livelihood at risk (Fafchamps, 1992; Dercon, 2005). It has long been argued that poor farmers in developing countries attempt to minimize their exposure to risk by growing their own necessities (Fafchamps, 1992; Kurosaki and Fafchamps, 2002), diversifying their activities (Walker and Ryan, 1990; Kurosaki, 1995), 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. Rose (2001) focused on the role of labor market participation both as an *ex ante* and an *ex post* response to *aggregate* shocks. She showed that households facing a greater rainfall risk were more likely to participate in the labor market (*ex ante* response) and 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 like India, it is important to distinguish two types of off-farm labor markets: agriculture and non-agriculture. Rose's (2001) analysis simply considered a single labor market, which, however, raises the following problem. The covariance between farming returns and agricultural wages is likely to be different from the covariance between farming returns and non-agricultural wages. 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. 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. At the same time, however, the covariance between wages and food prices also matters (Fafchamps, 1992; Kurosaki and Fafchamps, 2002; Kurosaki, 2006). For farmers for whom food security is an issue, agricultural work may nevertheless be more attractive than non-agricultural work if agricultural wages are paid in kind, since the monetary value of wages paid in paddy are positively correlated with the paddy price. We show that both of these considerations do indeed play a role in determining the off-farm labor supply of Indian farmers.

The remainder of the paper is organized as follows. Section 2 presents our theoretical model to explain how farmers decide to allocate their labor. The predictions of the model are tested using household data from rural areas of Bihar and Uttar Pradesh. The dataset is described in Section 3, while the regression and simulation results of a multivariate tobit model of labor allocation are presented in Section 4. Section 5 concludes the paper.

2. A Theoretical Model of Labor Allocation

In this section, we extract the essence of a theoretical model of Ito and Kurosaki (2006) to guide our empirical analysis. To stylize the conditions of low-income developing countries, we assume that there are only two consumption items: "food," which is also the main output in production; 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.

For simplicity, we fix the total labor supply at $\bar{L}$, ignoring the labor-leisure choice. The welfare of the household is measured by its expected utility, $E[v(y, p)]$, with the properties $v_y > 0$, $v_p < 0$, $v_{yy} < 0$, $v_{pp} < 0$, $v_{yp} > 0$, and $v_{yyy} > 0$. These properties 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 (Kurosaki, 2006). There are three different types of activity to which the household can allocate labor $\bar{L}$ (indicated by subscript j): own farming ($j = a$), agricultural wage work ($j = b$), and non-agricultural wage work ($j = c$). Since the total labor supply is fixed, the decision variables are the shares of each type of labor (ℓ_j). From each activity, the household obtains a labor return of $\theta_j f(\ell_j \bar{L})$, 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.

Thus, the household's optimization problem is to maximize $E[v(y, p, X_p)]$ with respect to ℓ_j subject to the budget constraint $y = y_0 + \sum_j \theta_j f_j(\ell_j \bar{L}, X_w)$, the time constraint $\sum_j \ell_j = 1$, and the non-negativity conditions for ℓ_j, $j = a, b, c$. X_p and X_w are vectors of household characteristics: X_p includes shifters of preferences with respect to risk exposure and food subsistence needs, while X_w includes shifters of household members' productivity, such as land, fixed capital, and human capital.

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

$$E[v_y\theta_j]\frac{\partial f_j}{\partial L} = E[v_y\theta_k]\frac{\partial f_k}{\partial L}, \qquad j \neq k, \tag{1}$$

where $\partial f_j/\partial L = \partial f_j/\partial(\ell_j\bar{L})$. Applying the implicit function theorem to (1), we obtain the reduced-form solution as

$$\ell_j^* = \ell_j(\bar{L}, X_p, X_w, \Sigma), \qquad j = a, b, c, \tag{2}$$

where Σ is the covariance matrix of θ_a, θ_b, θ_c, and θ_p. When θ_a and θ_b are positively correlated but θ_c is uncorrelated with θ_a, θ_b, and θ_p, we can derive our empirically verifiable relations:

$$\frac{\partial \ell_a^*}{\partial \sigma_a} < 0, \qquad \frac{\partial \ell_c^*}{\partial \sigma_a} > 0, \qquad \frac{\partial \ell_c^*}{\partial \sigma_a} > \frac{\partial \ell_b^*}{\partial \sigma_a}, \qquad \frac{\partial}{\partial \rho_b}\left(\frac{\partial \ell_c^*}{\partial \sigma_a} - \frac{\partial \ell_b^*}{\partial \sigma_a}\right) < 0, \tag{3}$$

where σ_a is the coefficient of variation of θ_a and ρ_p is the coefficient of correlation between θ_b and θ_p. The derivation of these results is given by Ito and Kurosaki (2006).

The first relation in (3) implies that the own-farm labor supply declines as production becomes riskier. However, the alternatives to own-farm work are not homogeneous. The second and third relations in (3) imply that it is non-agricultural wage work that absorbs a larger share of the displaced labor. Thus, we can empirically test *whether an increase in σ_a raises the non-agricultural wage work share more than it raises the agricultural wage work share.*

The last relation in (3) shows that the attractiveness of non-agricultural work relative to agricultural work declines when the correlation between the agricultural wage and the food price becomes positive. This reflects household considerations of food security, which is analyzed by Fafchamps (1992). Since wages 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). Thus, as an empirically verifiable prediction, we test *whether the positive effect of σ_a on the non-agricultural wage work share declines relative to that on the agricultural wage work share when the agricultural wage is paid in kind.*

3. Data

In the empirical part of this paper, we use data on agricultural households obtained from the *Survey of Living Conditions, Uttar Pradesh and Bihar*, which is one of the Living Standard Measurement Study (LSMS) surveys. Uttar Pradesh (UP) and Bihar are located in North India and are known for their high incidence of poverty. 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 four activities: (a) self-employment in agriculture, (b) wage work in agriculture, (c) wage work in non-agriculture, and (d) self-employment in non-agriculture.

Based on these four activities, we divide patterns of labor allocation into five categories (Table 1). Among the five, category A, households relying on self-employed work only, make up the largest group, accounting for 41.4% of the total, followed by households that combine own farming with wage work (pattern C, 36.3%). 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) or (c)' in the table). The table also shows that work in non-agriculture was more frequent than work in agriculture.

The lower half of Table 1 shows that farm households with income sources other than own farming have less land and more household members. 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. The column titled 'Annual labor supply' in Table 1 also shows that pure farm households ('(a) only') supply the smallest amount of labor per household. The smaller labor supply of these farm households indicates that their reservation wage is higher than that of other households.

Summary statistics of the variables used in the regression analysis are presented in Table 2. The dependent variables are the shares of the four different types of work. Since the four shares add up to 100% by definition, we drop the last category in the regression analysis.

Adopting a reduced-form approach, we regress the three dependent variables on household characteristics (X) and aggregate risk factors (σ_a and ρ_b). 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 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.

Controlling for X, we test the prediction from Section 2 with respect to σ_a and ρ_b using a basic and an extended model. As aggregate 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_rainfall*) is employed in both models.[1] Two further variables are included that capture aggregate risk factors. One is *Rainfall_shock*, which is intended to capture the *ex post* response of off-farm labor supply to production shocks. We would expect a positive coefficient on this variable if households increase their off-farm labor supply primarily as a result of a failure in rainfall. The other variable we include is *Irrig_village*, which is a village-level irrigation indicator. Since we already control for the productivity increase in own farming thanks to irrigation by including *Irrig_hh* (the household-level irrigation ratio), we expect the additional variable *Irrig_village* to capture the impact of irrigation in reducing the village-level production risk. In the extended model, the variable *Kindshare* (the village-level ratio of agricultural wages paid in kind) is calculated and its cross-term with *CV_rainfall* is included as a proxy for the correlation between the food price and agricultural wage shocks.

[1] See Ito and Kurosaki (2006). They show that the variation of rainfall is a relevant proxy because the deviation of rainfall in a district in a year from its yearly average precisely predicts the deviation of the agricultural production in the district.

4. Results

4.1. Determinants of Off-Farm Labor Supply

To estimate the determinants of off-farm labor supply, we employ a multivariate tobit model, since there are three dependent variables, all of which are censored at zero. The regression results are reported in Table 3.

Among household characteristics, *Land_own*, *Irrig_hh*, *Capital_agri*, and *Livestock* have a positive effect on the on-farm labor supply (ℓ_a) and a negative effect on the off-farm supply (ℓ_b and ℓ_c). Since all of these variables raise the productivity of own farming, they mainly correspond to X_w (productivity shifters). 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).

Turning to the variable of interest, *CV_rainfall*, we find that this has a significant negative impact on the on-farm labor supply (ℓ_a), confirming the first theoretical prediction of (3). In contrast, both ℓ_b and ℓ_c increase with *CV_rainfall*, but the magnitude of the increase is much larger for ℓ_c, off-farm non-agricultural work. Thus, the second and third theoretical predictions of (3) are also confirmed. Agricultural households facing a greater weather risk tend to divert more labor to off-farm work, mainly in non-agriculture. In contrast, while weather risk (*CV_rainfall*) has a significant impact, weather shocks do not: the coefficient on *Rainfall_shock* is not statistically significant, although it is positive in the regressions for both ℓ_b and ℓ_c. Our results are thus slightly different from Rose's result (2001) that weather shocks significantly increase the off-farm labor supply. The coefficient on *Irrig_village* is significantly negative in the regression for ℓ_c, indicating that the off-farm labor supply of farm households is smaller in villages with more stable farming production. From these results, we conclude that off-farm labor in the study region serves more as an *ex ante* income diversifying measure than as an *ex post* measure.

In order to examine the robustness of our results, we try out various alternative specifications (Table 4). First, the OLS results remain qualitatively unchanged, although the slope of *CV_rainfall* becomes smaller. Second, to test the last prediction of (3) that the attractiveness of non-agricultural work relative to agricultural work declines when the correlation between the food price and agricultural wages becomes positive, an interaction term between *CV_rainfall* and *Kindshare* is added in the extended model. To facilitate the interpretation of the coefficients, *Kindshare* is differenced from its mean. The inclusion of the cross-term does not affect the significance of the coefficient on *CV_rainfall* while the coefficient on the cross-term is significantly positive in the regression for ℓ_b. Therefore, when agricultural wages are paid in kind, the attractiveness of non-agricultural work relative to agricultural work declines among the sample households, as predicted theoretically.

4.2. A Simulation of the Impact of Weather Risk

In order to examine the economic significance of the effect of weather risk on off-farm labor supply, we run simulation exercises. 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 paper, we employ the procedure proposed by Cornick et al. (1994) and run Monte-Carlo simulations. Table 5 reports our simulation results. Despite the difference in methodology and data, our simulation results with respect to off-farm work (agricultural and non-agricultural work pooled; last column) are qualitatively similar to those obtained by Rose (2001).[2] Our results indicate that, when the weather risk increases (*CV_rainfall* increases from its minimum to its maximum), the percentage of households participating in off-farm wage work increases from 65% to 73%. 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 agricultural and non-agricultural labor markets. Doing so indicates that agricultural work increases by only 0.7 percentage points, but non-agricultural

[2]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.

work increases by 6.5 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 four rows provide the response of ℓ_j conditional on $\ell_j > 0$, which is a more correct measure of marginal changes in labor supply induced by an increase in weather risk. In the last four rows, the unconditional response of ℓ_j is shown, which is a more useful measure to predict total changes in the sample when the weather risk becomes more severe. Both show that the labor share allocated to off-farm work increases with the increase in *CV_rainfall* and the response of non-agricultural wage work is more substantial. These results thus confirm that off-farm work in the non-agricultural sector plays an important role in diversifying farm production risk.

5. Conclusion

This paper investigated the effects of weather risk on the off-farm labor supply of agricultural households in India. We tested the theoretical predictions that the impact of weather risk on the off-farm labor supply is larger in the case of non-agricultural than agricultural wage work because agricultural wages are likely to be more positively correlated with own farm income than non-agricultural wages, and that, if agricultural wages are paid in kind, the attractiveness of non-agricultural wage work decreases relative to agricultural work due to food security concerns on the part of poor farmers. These predictions were 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 mechanisms. This study shows that labor markets potentially 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.

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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.
A) Self-employment only			D) Self-emp. non-agric. and wage work		
(a) only	354	21.2%	(b) and (d)	13	0.8%
(d) only	16	1.0%	(c) and (d)	12	0.7%
(a) and (d)	322	19.3%	(b), (c), and (d)	13	0.8%
A) Sub-total	692	41.4%	D) Sub-total	38	2.3%
B) Wage work only			E) Other		
(b) only	29	1.7%	(a), (b), and (d)	40	2.4%
(c) only	38	2.3%	(a), (c), and (d)	123	7.4%
(b) and (c)	29	1.7%	(a),(b),(c),(d)	74	4.4%
B) Sub-total	96	5.7%	E) Sub-total	237	14.2%
C) Self-emp. agric. and wage work			Including (a)	1520	91.0%
(a) and (b)	90	5.4%	Including (b)	473	28.3%
(a) and (c)	332	19.9%	Including (c)	806	48.3%
(a), (b), and (c)	185	11.1%	Including (b) or (c)	978	58.6%
C) Sub-total	607	36.3%	Grand total (A-E)	1670	100%

II. Household characteristics by labor allocation pattern

	No. of obs.	Lower caste[2] (%)	Annual labor supply[2] (hrs)	No. of working members[2]
(a) only	354	67.51	1910.10	1.84
(a) and (c)	332	72.59	3547.81	2.56
(a) and (d)	322	73.60	3391.59	2.34
(a), (b), and (c)	185	95.14	3672.14	2.85

	No. of working age members[3]	No. of non-working age mem.[2]	Size of farmland owned by the household (acres)
Total	3.60	3.06	2.71
(a) only	3.21	2.56	4.51
(a) and (c)	4.10	3.04	2.59
(a) and (d)	3.81	3.41	2.87
(a), (b), and (c)	3.24	3.19	1.18

Notes: (1) (a) = Self-employment in agriculture; (b) = Wage work in agriculture; (c) = Wage work in non-agriculture; (d) = Self-employment in non-agriculture.
(2) The share of households belonging neither to a middle or upper Hindu caste.
(3) The reported figures are the averages for all households. '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. Working-age members are defined as those aged between 15 and 60.

Table 2: Summary Statistics of Regression Variables

Variable	Unit	Mean	Std. Dev.	Min.	Max.
Dependent variables: Labor hour shares (ℓ_j)					
(a) Self-emp., agriculture	%	44.92	36.13	0	100
(b) Wage work, agriculture	%	12.39	24.78	0	100
(c) Wage work, non-agric.	%	25.75	32.44	0	100
(d) Self-emp., non-agric.	%	16.95	27.96	0	99.37
Explanatory variables: Household characteristics (X)					
Land_own$^{(1)}$	acre	2.70	4.71	0	93
Irrig_hh$^{(1)}$	%	80.07	32.72	0	100
Capital_agri	Rs.	7226.82	30493.54	0	373600
Livestock	Rs.	7183.27	9545.76	0	150000
Education$^{(2)}$	year	3.52	3.60	0	18.5
Working-age_males$^{(2)}$	person	1.89	1.17	0	7
Working-age_females$^{(2)}$	person	1.72	1.06	0	8
Non-working-age_members$^{(2)}$	person	3.06	2.16	0	17
Dummy_landown$^{(1)}$	-	0.95			
Gross_lending$^{(6)}$	Rs.	513.36	4752.34	0	150000
Gross_borrowing$^{(6)}$	Rs.	3833.29	10151.58	0	170000
Caste dummies ('Upper' as the reference category)					
Middle	-	0.02			
Backward_agri	-	0.33			
Backward_other	-	0.18			
Scheduled_caste	-	0.22			
Muslim_upper	-	0.04			
Muslim_lower	-	0.05			
Explanatory variables: Aggregate risk factors (σ_a, ρ_b)					
CV_rainfall$^{(4)}$	-	0.29	0.07	0.13	0.39
Rainfall_shock$^{(4)}$	mm	26.16	64.56	-57.04	166.89
Irrig_village$^{(5)}$	-	3.80	1.19	1	5
Kindshare$^{(3)}$	-	0.159	0.136	0	0.569
Explanatory variables: Other controls					
UP_state_dummy	-	0.61			

Notes: (1) The sample is farm households, including pure tenant farmers who do not own land. 'Land_own' is the size of farmland owned by the household. 'Dummy_landown' is based on 'Land_own'. 'Irrig_hh' is the size of irrigated land owned by the household divided by 'Land_own'.
(2) 'Education' is the average number of schooling years among working-age adults.
(3) In the regression, the deviation from the mean is used.
(4) The coefficient of variation ('CV_rainfall') was calculated based on ten-year rainfall data at the district level (1990-1999). 'Rainfall_shock' was calculated as the deviation of rainfall in 1997, the year of the LSMS survey, from the ten-year average.
(5) 'Irrig_village' is an indicator variable based on the village-level irrigation ratio (the size of irrigated farmland divided by the size of total farmland in the village), taking 1 (0%), 2 (1-25%), 3 (26-50%), 4 (51-75%), and 5 (above).
(6) Including informal credit from landlords, employers, private moneylenders, relatives, and friends.

Table 3: Determinants of Labor Supply

	(a) Self-emp., agriculture		(b) Wage work, agriculture		(c) Wage work, non-agric.	
Household characteristics (X)						
Land_own	1.67	(3.14)***	-2.93	(3.02)***	-1.56	(3.84)***
Irrig_hh	0.09	(2.72)***	-0.23	(4.77)***	-0.01	(0.15)
Capital_agri/10^4	0.33	(0.74)	-1.07	(0.63)	-1.96	(2.89)***
Livestock/10^4	4.73	(4.15)***	-2.65	(1.26)	-5.68	(3.18)***
Education	-0.15	(0.49)	-3.36	(5.68)***	0.51	(0.96)
Working-age_males	-3.83	(4.25)***	-3.80	(2.40)**	10.05	(6.59)***
Working-age_females	-0.16	(0.15)	-0.65	(0.34)	1.88	(1.05)
Non-working-age_mem.	-1.28	(3.19)***	1.60	(2.10)**	1.21	(1.61)
Dummy_landown	7.40	(1.86)*	-13.64	(2.11)**	-1.93	(0.30)
Gross_lending/10^4	-3.86	(2.83)***	-33.94	(1.22)	-6.12	(1.49)
Gross_borrowing/10^4	0.002	(0.00)	-3.38	(1.31)	-3.65	(1.83)*
Caste dummies						
Middle	-8.05	(1.35)	1.68	(0.10)	-13.27	(1.09)
Backward_agri	4.02	(1.26)	23.93	(3.11)***	-9.71	(1.78)*
Backward_other	-10.47	(2.94)***	27.50	(3.47)***	2.11	(0.35)
Scheduled_caste	-17.47	(4.95)***	62.04	(8.19)***	2.74	(0.46)
Muslim_upper	-9.94	(1.68)*	9.65	(0.82)	3.38	(0.34)
Muslim_lower	-23.55	(4.60)***	5.33	(0.46)	-2.89	(0.31)
Aggregate risk factors (σ_a, ρ_b)						
CV_rainfall	-73.11	(5.08)***	2.85	(0.11)	48.06	(2.02)**
Rainfall_shock/10^2	1.73	(0.89)	5.40	(1.53)	1.47	(0.42)
Irrig_village	-0.30	(0.37)	0.79	(0.58)	-2.75	(2.09)**
Other controls						
UP_state_dummy	-5.33	(2.06)**	8.25	(1.71)*	18.72	(4.09)***
Intercept	65.05	(8.82)***	-10.25	(0.74)	-23.91	(1.91)*
Standard error	34.16	(63.28)***	47.46	(31.71)***	53.98	(46.96)***
Correlation matrix	1.00		-0.48	(17.29)***	-0.61	(34.25)***
			1.00		0.01	(0.19)
					1.00	

Notes: (1) Estimated using a multivariate tobit specification.
(2) Numbers in parentheses are z-values based on Huber-White heteroscedasticity-consistent standard errors.
(3) No. of obs. = 1654 (To make the estimation feasible, 16 households in Table 1 who supplied labor to self-employment in non-agriculture only were excluded).
(4) Log-likelihood = -15113.26.
(5) Likelihood ratio tests: H_0 zero slope: $\chi^2(63)$= 866.46; H_0 all non-off-diagonal elements of the correlation matrix are zero: $\chi^2(3)$=907.37; H_0 all three coefficients on 'CV_rainfall' are zero: $\chi^2(3)$= 30.90; H_0 all three coefficients on 'Rainfall_shock' are zero: $\chi^2(3)$=7.42.

Table 4: Labor Supply and Rainfall Risk

	(a) Self-emp., agriculture		(b) Wage work, agriculture		(c) Wage work, non-agriculture	
Without cross effects, multivariate tobit (Table 3)						
CV_rainfall	-73.11	(5.08)***	2.85	(0.11)	48.06	(2.02)**
Rainfall_shock/10^2	1.73	(0.89)	5.40	(1.53)	1.47	(0.42)
Without cross effects, OLS						
CV_rainfall	-62.38	(4.53)***	19.22	(1.94)*	28.96	(2.35)**
Rainfall_shock/10^2	1.68	(0.90)	3.29	(2.75)***	-0.51	(0.29)
With cross effects, multivariate tobit						
CV_rainfall	-74.16	(5.15)***	-30.77	(1.20)	52.44	(2.18)**
CV_rainfall*Kindshare	7.19	(0.31)	198.10	(4.76)***	-27.07	(0.66)
Rainfall_shock/10^2	1.57	(0.78)	-0.02	(0.01)	2.14	(0.59)
With cross effects, OLS						
CV_rainfall	-62.55	(4.40)***	12.45	(1.26)	33.36	(2.62)***
CV_rainfall*Kindshare	1.21	(0.05)	46.77	(3.19) ***	-30.37	(1.50)
Rainfall_shock/10^2	1.65	(0.86)	2.19	(1.85)*	0.20	(0.11)

Notes: All four specifications are estimated with other variables included, such as household characteristics and a dummy for Uttar Pradesh. Coefficient estimates on these variables have been dropped for brevity but are available on request. Numbers in parentheses are z-values (t-values) based on Huber-White heteroscedasticity-consistent standard errors.

Table 5: Off-Farm Labor Supply Simulation

A. Simulation of Wage-Labor Market Participation		Wage work, agriculture $\Pr(\ell_b > 0)$	Wage work, non-agricul. $\Pr(\ell_c > 0)$	Wage work, any type $\Pr(\ell_b + \ell_c > 0)$
			This paper	
(a)	CV_rainfall=0.13(Min.)	0.296	0.455	0.646
	CV_rainfall=0.39(Max.)	0.303	0.570	0.729
(b)	Rainfall_shock=-2Std.Dev.	0.258	0.510	0.663
	Rainfall_shock=+2Std.Dev.	0.341	0.546	0.731
			Rose (2001), Table 3	
(a)	CV_rainfall=0.16(Min.)	-	-	0.32
	CV_rainfall=0.91(Max.)	-	-	0.51
(b)	Rainfall_shock=-2Std.Dev.	-	-	0.28
	Rainfall_shock=+2Std.Dev.	-	-	0.33

B. Simulation of Labor Supply Shares		(a) Self-emp., agriculture	(b) Wage work, agriculture	(c) Wage work, non-agricul.
		$E(\ell_a \mid \ell_a > 0)$	$E(\ell_b \mid \ell_b > 0)$	$E(\ell_c \mid \ell_c > 0)$
(a)	CV_rainfall=0.13(Min.)	60.08	30.45	42.07
	CV_rainfall=0.39(Max.)	46.40	30.65	46.77
(b)	Rainfall_shock=-2Std.Dev.	49.88	28.76	44.22
	Rainfall_shock=+2Std.Dev.	53.02	32.54	45.67
		$E(\ell_a)$	$E(\ell_b)$	$E(\ell_c)$
(a)	CV_rainfall=0.13(Min.)	51.58	11.33	20.31
	CV_rainfall=0.39(Max.)	35.51	11.51	28.05
(b)	Rainfall_shock=-2Std.Dev.	39.66	9.44	23.79
	Rainfall_shock=+2Std.Dev.	43.26	13.75	26.26

Notes: $E(\ell_j|\ell_j > 0) = Z\beta_j + \sigma_j \left[\frac{\phi(Z\beta_j/\sigma_j)}{\Phi(Z\beta_j/\sigma_j)}\right]$, $E(\ell_j) = E(\ell_j|\ell_j > 0) \times \Pr(\ell_j > 0)$, where $\Pr(\ell_j > 0)$ is estimated from the upper portion of Table 5. Simulations are based on the estimation results from Table 3. See Ito and Kurosaki (2006) for the full description of these simulations.