Migration and Risk

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Migration is an important aspect of development

A. Permanent migration is a key mechanism for eradicating spatial mis-allocations, as measured by persistent wage and price differentials.

B. Permanent migration is a key component of the 'structural transformation' of an economy.

C. Temporary migration is an important income-smoothing mechanism.

Are levels of migration too high? Too low?

What are the barriers to migration, if too low?

Risk plays a major role in the analysis of migration:

A. Risk at destination affects migration (old literature):

   Probability of not getting a job; not getting a high wage offer.

B. Risk at origin (new literature):

   Risk-coping institutions may affect migration choices.

   Origin income shocks affect temporary migration choices.

   Migration opportunities may affect risk-coping institutions.

Rural Risk-Coping: Interdependent Choices

Sector/timing	Income/production	Consumption
ex ante	Technology choice Crop choice Crop diversification Irrigation Occup. diversification permanent *migration* Anticipatory *migration*	Save Buy formal insurance Network insurance arr. marital *migration*
ex post	Labor supply *Migration*	Borrow Sell assets (dissave) Transfers

Here I will traverse the non-macro literature on permanent and temporary migration incorporating risk, starting with the 1970 Hariss and Todaro model, up through studies that are just being completed.

H-T is a benchmark: voted in the top 20 of all *AER* articles in a 100-year period.

> Starts with a puzzle, and ends solving the puzzle and indicating policy choices.

We will see what new puzzles and policy issues are addressed, where the emphasis has changed, where the inconsistencies are across studies, what are future fruitful inquiries.

Outline

1. Permanent migration

Puzzles:	Too much in Africa; too little for men in India but almost universal for women in India.
Policies:	Effects of employment schemes at origin and destination on migration.

2. *Ex post* and anticipatory temporary migration

Policies:	Effects of employment schemes, reduced migration costs, forecasts on: migration, risk-sharing, risk-taking, equilibrium wages.

Studies:

Harris, John R. and Michael Todaro, “Migration, Unemployment and Development: A Two-Sector Analysis” (*AER* 1970).
Rosenzweig, Mark and Oded Stark, “Consumption Smoothing, Migration, and Marriage: Evidence from Rural India,” *JPE* 97(4): 905-926, 1989.
Munshi, Kaivan and Mark Rosenzweig “Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap”*AER* 106(1): 46-98, 2016.
Morten, Melanie “Temporary Migration and Endogenous Risk-Sharing in Village India,” Stanford University, 2017.
G. Bryan, S. Chowdhury and A. M. Mobarak, “Under-investment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh” *Econometrica* 82(5): 1671-1748, 2014.
Meghir, Costas; A. Mushfiq Mobarak; Mommaerts, Corina; Morten, Melanie (M^4). “ Migration and Consumption Insurance in Bangladesh,” Yale University, 2017.
Rosenzweig, Mark and Christopher Udry, “Rural Risk and Anticipatory Migration,” Yale University, 2017.

Rural-Urban Migration and Urban Unemployment

Puzzle: Sustained high migration to urban areas in sub-Saharan Africa despite high urban unemployment.

The Harris-Todaro Model (1970): risk = probability of <u>urban</u> unemployment

A. General-Equilibrium with two sectors - urban and rural.

B. Perfectly competitive markets in both sectors, no rural risk!

C. One distortion: a fixed minimum urban wage W^* that binds, so there is urban unemployment u.

C. A rural migrant getting an urban job is random.

Key implication: migration depends on the *expected* urban wage:

$$\tilde{W} = uW^*$$

Policy questions posed: when urban jobs are increased, what happens to:

A. Rural-urban migration.

B. The number of urban unemployed.

C. The urban unemployment rate.

Agricultural sector, with fixed land L and capital K endowments:

$$X_A = q(N_A, L, K_A) \qquad q'>0,\ q''<0$$

where N_A = rural labor (the only variable)

X_A = agricultural output

Urban manufacturing sector with a fixed capital endowmnet:

$$X_M = f(N_M, K_M) \qquad f'>0,\ f''<0$$

where N_M = labor used in manufacturing

X_M = output of manufacturing sector

Price determination (terms of trade):

$$P = \rho(X_{\mathrm{M}}/X_{\mathrm{A}}) \qquad\qquad \rho' > 0$$

so manufactured goods serve as numeraire.

Wages in each sector:

$$W_{\mathrm{A}} = Pq'$$

$$W_{\mathrm{M}} = f' = \mathrm{W}^* \text{ (binding minimum wage)}$$

The urban expected wage:

$$\tilde{W} = W^* N_M / N_u$$, where N_u = total urban labor force

Labor constraint:

$$N_A + N_u = \bar{N}_R + \bar{N}_u$$

Equilibrium condition:

$$W_A = \tilde{W}$$

based on the assumption that migration depends positively on the expected urban-rural wage differential, so that

$$\dot{N}_u = \varphi(W * N_M / N_u - Pq')$$

with $\varphi' > 0$, and stability requires that $d\dot{N}_u / dN_u < 0$.

So, migration is a disequilibrium phenomenon, stopping when the expected urban wage equals the rural wage, the equilibrium condition.

So, what happens when there is an expansion of urban manufacturing jobs?

Differentiate the equilibrium condition wrt N_M:

$$dN_u / dN_M$$

$$= [(W^* / N_u) - (\rho q' f' / \eta_A X_M)] / [(W^* N_M / N_u) - \rho q'' + (\rho(q') / \eta_A X_A)]$$

where η_A = price elasticity of demand for the agricultural good X_A

The issue is whether $dN_u/dN_M > 1$:

when the manufacturing sector expands by one job does more than one migrant come to the city (unemployment ↑).

Actually, there is no prediction.

Can show that the expression is larger the higher is W* and η_A, but lower the greater are q' and f' and q'', so

The higher is the wage differential and the less sensitive are prices and marginal products the greater will be the migration response.

Conclusion: "with parameter values relevant for many African economies...[dN_u/dN_M] will exceed unity."

Lessons for policies:

A. Subsidies to manufacturing to eliminate unemployment:

   Raises expected wage, induces more migration increasing the marginal product of agriculture q' to $W^* > f'$, so inefficient.

B. Some subsidy is welfare improving, but second best is with unemployment and $f' > q'$ in equilibrium, if $dN_u/dN_M > 1$.

C. Given that W* is set above the free-market equilibrium wage, the optimal policy is a combination of manufacturing wage subsidies and migration restrictions!

D. Or agricultural development that raises q' $\Rightarrow$ reverse flow.

Permanent Migration and Rural Risk

Puzzles:

A. Permanent migration rates for Indian rural *women* are high.

B. Permanent migration rates for rural *men* in India are unusually low and the real expected urban-rural wage gap is high.

India: among the lowest rates of urban-rural migration of any large country, highest r-u wage gaps.

Studies by Rosenzweig and Stark and Munshi and Rosenzweig focus on rural risk as fundamental.

How risky is agriculture, in India?

One of the best data sets for measuring risk and understanding its consequences (used for migration studies as well):

The ICRISAT VLS:

Panel of farmers and landless workers in three phases:

A. 1975-84: 6-10 villages with 30 farmers in each village.

B. 2001-2008: same 10 villages as in 1984.

C. 2009-2014: expanded to 20 villages.

Two important features:

High frequency data collection (every three weeks):

Obtain accurate counts of temporary migration.

10-year panel:

Enables observation on fluctuations in income and consumption, and risk-coping.

Look at:

Variability in average farm profits by village (1975-83).

Estimates of variability in investment returns (2005-11).

Figure 1

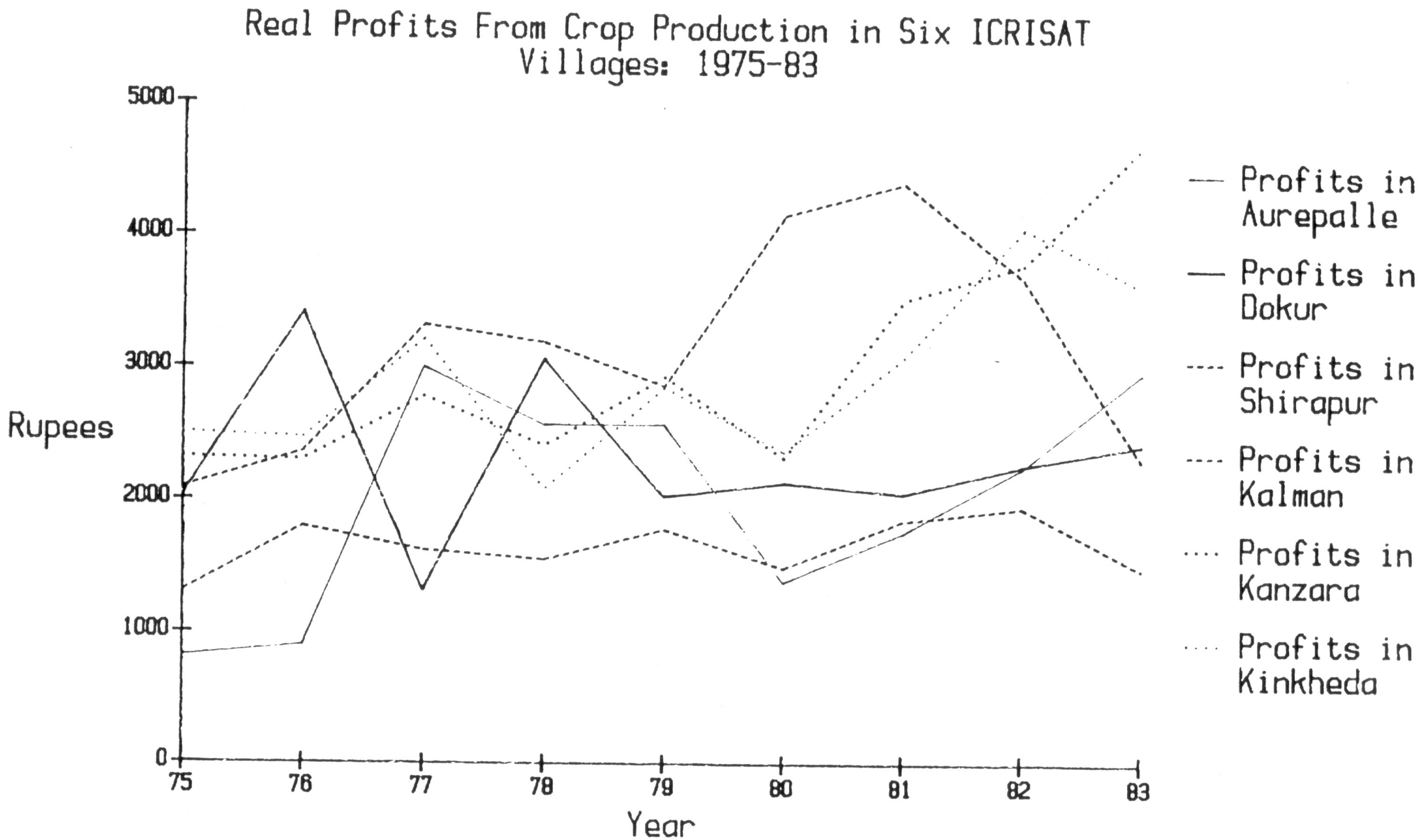
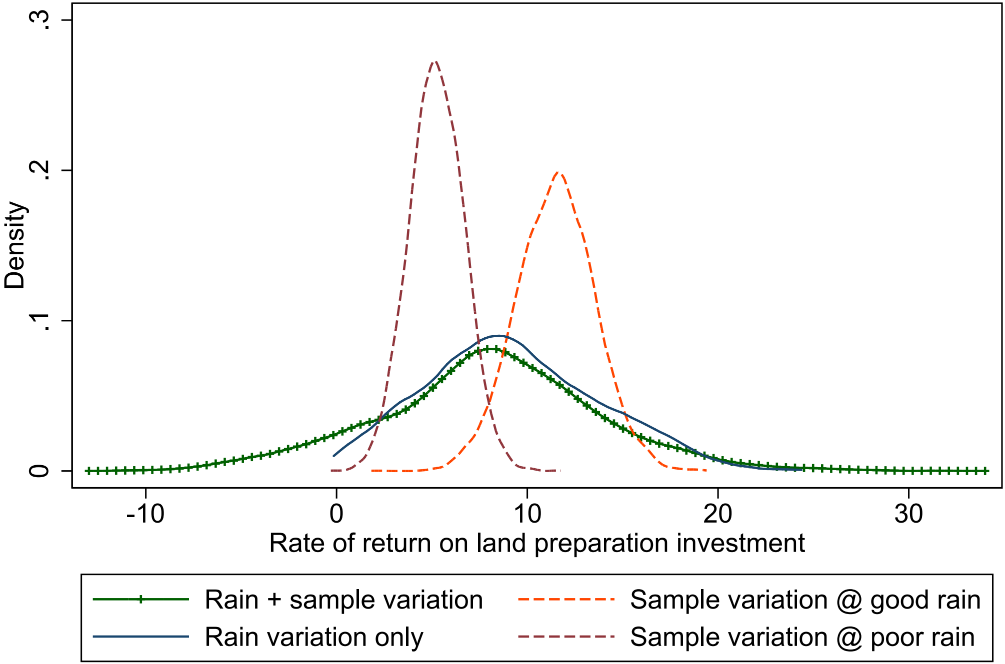

Real Profits From Crop Production in Six ICRISAT Villages: 1975-83
Rupees
5000
4000
3000
2000
1000
0
75
76
77
78
79
80
81
82
83
Year
Profits in Aurepalle
Profits in Dokur
Profits in Shirapur
Profits in Kalman
Profits in Kanzara
Profits in Kinkheda

Fig. X: Distribution of Returns and Weather Shocks, India



Risk-Coping and Marital Arrangements: India

The efficient risk-sharing model eliminates idiosyncratic risk - independent shocks to households - but not aggregate community-level risk.

Given spatial covariance of risk, especially in agriculture, want partners in risk pooling arrangement who are spatially separated.

> Household migrants: evidence from Africa (Lucas and Stark, JPE 1986) that remittances compensatory.

Rosenzweig and Stark (*JPE* 1989)

Basic ideas:

A. Covariance of risk is a major problem: weather.

B. *Patrilocal exogamy*: Marriages of women create (reinforce) ties among spatially-separated households.

Motivation: Caldwell and Caldwell anthropological study showing principle source of transfers to drought-stricken villages: in-laws

Study provides evidence on the source of transfers, on distance and risk covariance, on role of marriage in reducing consumption variability relative to income variability.

Data:

A. ICRISAT VLS: 1975-1984

Panel survey of farmers and landless in 6-10 villages.

B. Special survey was carried out of the heads of households in the 10 ICRISAT villages in 1984 - 115 marriages

Obtained the locations of:

The husbands of all the daughters of the head.

The locations of origin of all daughters-in-law.

The locations of origin of the head's wife.

Findings:

A. 92.2% of married women came from or went to another village (exogamy).

B. The average distance between the origin and destination village = 33 km (sd=60), max dist = 750km.

C. In households with two or more married women (daughters or daughters-in-law) 94% not from or located in same village.

D. Only 14 of 115 marriages involved partners who were not blood relatives (all same sub-caste).

E. 59% of transfers came from outside the village.

Does distance matter for reducing the covariance of risk?

Findings on spatial covariance:

Used times-series information on daily rainfall, profits, wages in the 6 ICRISAT villages with ten years of data.

Measurement: distance d_{ij} between each of the village pairs i and j in the 6 villages = 15 independent pairs.

correlation coefficient ρ_{ijk} for each variable k between village i and village j

Estimate:

$$\rho_{ijk} = \beta d_{ij} + \varepsilon_{ij}, \qquad \text{where } k = \text{rainfall, profits, wages.}$$

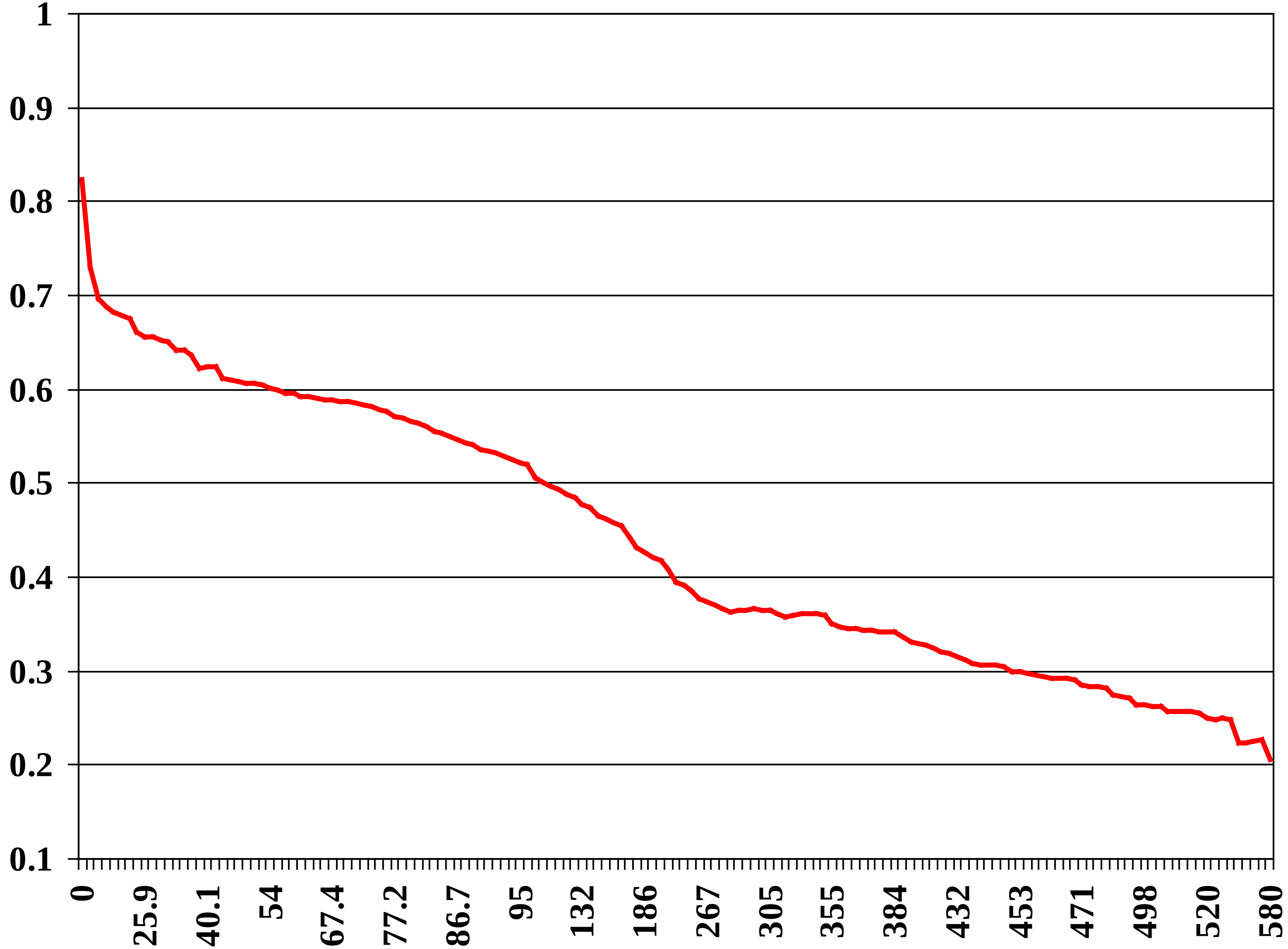
Table

Covariate Risk and Distance: Estimates of the Effect of Inter-Village Distance on the Pair-wise Inter-village Transformed Correlation for Six ICRISAT Villages, 1975-84

Variable	Daily Rainfall	Mean Real Profits	Real Daily Wages
Distance between villages (km x 10^{-3})	-0.122***	-0.912***	-0.0998**
	(0.0224)	(0.0368)	(0.0509)
R^2	.694	.322	.227
N	15	15	15

Dependent variable = 0.5log[(1 + r)/(1 - r)]. Standard errors in parentheses)

Figure 1:Lowess-Smoothed Relationship between Inter-Village Distance (Km) and June-August Rainfall Correlation, Andhra Pradesh and Uttar Pradesh 1999-2006



Directly testing for the relationship between consumption-smoothing and marriage:

Compute the variance in consumption σ_c^2 and farm profits σ_π^2 for each ICRISAT farm household over 10 years.

Want to know the relationship between a household's consumption variability and its profit variability, and how it is mitigated by household characteristics.

Specification:

$$\sigma_c^2 = \delta_1\sigma_\pi^2 + \delta_2\sigma_\pi^2 \text{ x (wealth)} + \delta_3\sigma_\pi^2 \text{ x (\# of marriages)} + \delta_4\sigma_\pi^2 \text{ x } (d)$$

d = mean marital distance $\delta_1 > 0$; δ_2, δ_3, $\delta_4 < 0$

Table
Consumption Smoothing and Marital Migration:
Estimates of the Determinants of the Inter-temporal Variance of Real Food Expenditures
in Farm Households in the Six ICRISAT Villages, 1975-84

Variable	(1)	(2)	(3)
Profit σ^2	0.114***	0.229***	0.227***
	(0.00765)	(0.0289)	(0.0316)
Inherited wealth (x 10^{-6}) x profit σ^2	-0.147***	-0.107***	-0.197***
	(0.0360)	(0.0215)	(0.0435)
Number of married women x profit σ^2	-	-0.0346***	-0.0340***
		(0.0123)	(0.0173)
Mean marriage distance (km x 10^{-3}) x profit σ^2	-	-0.228***	-0.231***
		(0.0529)	(0.0533)
Number of male migrants x profit σ^2	-	-0.00719	-0.00695
		(0.00545)	(0.00675)
Includes village fixed effects	Y	Y	Y
Includes adult male and females x profit σ^2	N	N	Y

Dependent variable = real food expenditure σ^2

The household-specific mechanisms of *ex post* consumption smoothing:

A. Temporary migrants.

B. Occupational portfolio - jobs with constant wages (attached farm laborer).

B. Extend marital distance.

Households facing more exogenous risk and with lower wealth will more likely use these mechanisms.

Measurement of predicted household risk:

$\sigma_{\pi}^{2} = \sigma_{R}^{2}$ x household *inherited* dry and irrigated own land

TABLE 5

EFFECTS OF AGRICULTURAL PROFIT LEVELS AND PROFIT VARIABILITY ON HOUSEHOLD LABOR FORCE AND MARITAL ARRANGEMENTS

	DEPENDENT VARIABLE (Estimation Procedure)							
	Number of Migrants (Two-Stage Maximum Likelihood Tobit)		Attached Laborer/ Salaried Worker (Two-Stage Maximum Likelihood Probit)		Mean Marriage Distance (Two-Stage Least Squares)		Value of Landholdings of Head's Father-in-Law* (Two-Stage Maximum Likelihood Tobit)	
Profit variance†	1.32	4.67	−.0381	.137	.707	54.8	.00490	−.0580
	(5.26)	(2.60)	(1.85)	(2.05)	(2.98)	(.52)‡	(.51)	(1.37)
Profit mean† ($\times 10^{-5}$)	. . .	−.152	. . .	−7.40	. . .	2.98	. . .	.00126
		(.33)		(2.66)		(.15)‡		(1.58)
Value of inheritance ($\times 10^{-4}$)	−2.57	−.0356	.0286	−.134	−2.21	−2.03	7,261§	8,618
	(2.20)	(.21)	(.59)	(1.41)	(1.85)	(1.32)	(1.16)	(1.72)
Constant	−.280	−6.42	.287	5.94	−10.31	−7.71	88,964	129,574
	(1.51)	(3.23)	(.37)	(2.41)	(.47)	(.30)	(.95)	(1.25)
χ^2, F	37.8	32.9	10.2	21.0	4.45	3.87	8.75	11.2
Hausman-Wu	9.93	7.08	2.46	13.1	19.4	10.6	2.12	2.48

NOTE.—Asymptotic t-ratios are in parentheses beneath coefficients.
* In 1983 rupees.
† Endogenous variable. Instruments include village-level means and variances of rainfall in July–October 1975–84, and interactions between the rainfall statistics and head's dry and irrigated landholdings at inheritance.
‡ Jointly significant: $F(2, 59) = 5.78$.
§ Inheritance of head's father (in 1983 rupees).

Permanent Migration of Men, Networks, Rural Risk and the Urban-Rural Wage Gap

Puzzle: The low male migration rates in India and the seemingly large gains from migrating: large rural-urban wage gap.

First document the facts, showing migration rates and the wage gap, in comparison to the countries.

India is an outlier.

Then model, tests and policy simulations:

Munshi and Rosenzweig (*AE*R, 2016)

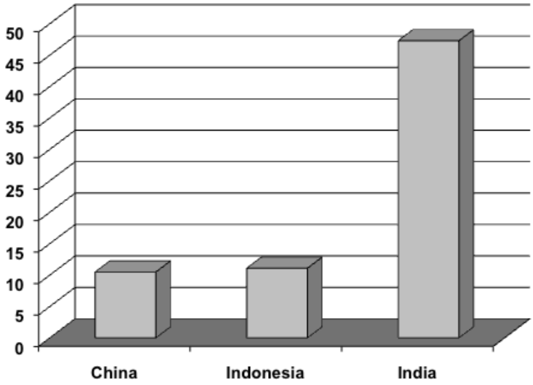
Key is the success of caste networks in smoothing consumption.

Table 1
Rural-Urban Wage and Expected Wage Gaps in India in 2004
(Daily Wages, Rupees)

Sector	Nominal	PPP-adjusted (rural consumption)	PPP & unemployment-adjusted
Urban	62.7	54.1	51.2
Rural	42.5	42.5	38.8
% Gain	47.3	27.1	31.9

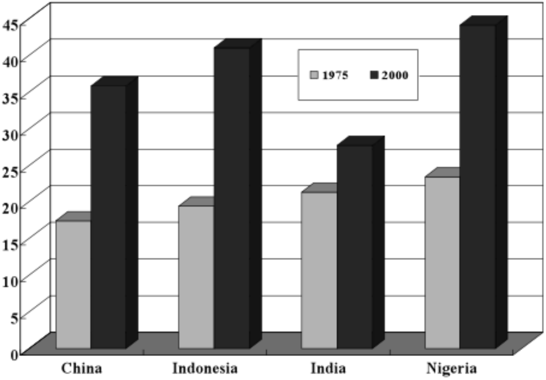
Source: National Sample Survey (NSS)

Figure 1: Rural-Urban Wage Gap, by Country



Source: 2006 Chinese mini-census, 2007 IFLS, 2004 NSS

Figure 4: Change in Percent Urbanized, by Country, 1975-2000



Source: UNDP 2002

The basic idea for the low mobility of men:

Combination of well-functioning rural insurance networks and the absence of formal insurance (Banerjee and Newman 1998).

In rural India, insurance networks are organized along caste lines.

Commitment and information problems are greater for households with male migrants.

If the resulting loss in network insurance is sufficiently large, and alternative sources of insurance are unavailable, then large wage gaps could persist without generating a flow of workers to higher wage areas.

Table 2: Participation in the Caste-Based Insurance Arrangement

Survey year:	1982	1999
	(1)	(2)
Households participating (%)	25.44	19.62
Percent of income sent	5.28	8.74
Percent of income received	19.06	40.26
Number of observations	4981	7405

Source: Rural Economic Development Survey (REDS) 1982 and 1999

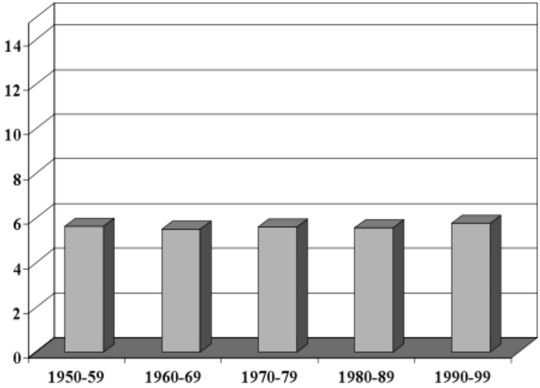
Table 3: Percent of Loans by Purpose and Source

Data source:	1982 REDS				
Purpose:	investment	operating expenses	contingencies	consumption expenses	all
	(1)	(2)	(3)	(4)	(5)
Sources:					
Bank	64.11	80.80	27.58	25.12	64.61
Caste	16.97	6.07	42.65	23.12	13.87
Friends	2.11	11.29	2.31	4.33	7.84
Employer	5.08	0.49	21.15	15.22	5.62
Moneylender	11.64	1.27	5.05	31.85	7.85
Other	0.02	0.07	1.27	0.37	0.22
Total	100.00	100.00	100.00	100.00	100.00

Table 4: Percent of Loans by Type and Source

Data source:	1982 REDS			2005 IHDS
Loan type:	without interest	without collateral	without collateral or interest	without interest
	(1)	(2)	(3)	(4)
Sources:				
Bank	0.57	23.43	0.38	0.00
Caste	28.99	60.27	20.38	44.62
Friends	9.35	91.72	3.89	21.5
Employer	0.44	65.69	0.44	10.75
Moneylender	0.00	98.71	0.00	0.27

Figure 5: Change in Out-Marriage Percent in Rural India, 1950- 1999



Source: 1999 REDS

Testing

The simplest test of the hypothesis that the potential loss in network services restricts mobility in India would be to compare migration-rates in populations with and without caste-based insurance.

This exercise is infeasible, given the pervasiveness of caste networks.

Thus, look *within* the caste and theoretically identify which households benefit less (more) from caste-based insurance.

> The test is whether those households are more (less) likely to have migrant members.

The Model

The literature on mutual insurance is concerned with *ex post* risk-sharing, taking the size of the network and the income sharing rule as given.

To derive the connection between networks and permanent migration, it is necessary to derive *ex ante* participation and the sharing rule (which determines which households choose to stay).

Indeed, it is assumed that complete risk-sharing can be maintained *ex post*.

> Consistent with high levels of risk-sharing documented in India and other developing countries.

Income generation and the migration decision:

The decision-making unit is the household, which consists of multiple earners.

Each household derives income from its local (rural) activities.

Income varies independently across households in the community and over time.

In addition, one or more members of the household receive a job opportunity in the city.

The key decision is whether or not to send them to the city.

Risk-sharing in the community-based network:

Ex post commitment is supported by social sanctions.

These sanctions - exclusion - are less effective when someone from the household has migrated to the city.

With full risk-sharing, each household is either in the network or out of the network.

It is assumed that households with migrants cannot commit to reciprocating at the level needed for full risk-sharing and so will be excluded from the network.

And the migrant's income is private information: migrant household has an incentive to under-report income *ex post*.

The mechanics of the model:

Each household has logarithmic preferences.

This implies that the expected utility from consumption, C, can be expressed as an additively separable function of mean consumption, M, and normalized risk, R ($\equiv V/M^2$),

$$EU(C) = \log(M) - 1/2R$$

With full risk-sharing and log preferences, each household's consumption is a fixed fraction of total income in each state of nature when all households are identical (equal sharing rule).

With k income classes, then there is a fixed rule for each class, but needs to be determined.

The participation decision:

The household will choose to participate in the network and remain in the village if

$$\log(M_I) - 1/2(V_I/M^2_I) \geq \log(M_A) - 1/2\beta(V_A/M^2_A) + \varepsilon$$

M_A, V_A = mean and variance of household <u>income</u> if all members remain in the village.

M_I, V_I = mean and variance of household <u>consumption</u> if all members remain in the village.

$M_A(1 + \log(1 + \varepsilon^*))$ = household mean income when one or more members migrate to the city. β = change in income risk with migration (lower covariance, alternative insurance).

The equal sharing rule (homogeneous group) implies that

$$M_I = M_A$$

$$V_I = V_A/N$$

Thus,

A. Larger networks are more effective in consumption-smoothing.

B. There is a strategic element to the participation decision because the gain from insurance depends on the number of participants.

Need to solve this fixed-point problem: unique equilibrium.

To solve the fixed-point problem:

First derive the threshold ε_I at which the participation condition holds with equality.

Assume there is a distribution (properties defined) characterized by the function $F(\varepsilon)$.

Then set $\mathrm{F}(\varepsilon_I)$ to be equal to N/P.

$$N/P = F(1/2\beta R_A - 1/2R_I),$$

noting that R_I is a function of N.

Key is that there is inequality within a community.

Divide the community into K equal sized groups of P_k.

With log preferences and full risk-sharing, $C_{ks}/C_{Ks} = \lambda_k$.

Then there is a fixed point condition for each income class:

$$N_k / P_k = F(\log(M_{Ik}) - \log(M_{Ak}), 1/2\beta R_A - 1/2R_I).$$

Thus, need to know λ_k to solve for N_k.

Assume that the social planner maximizes the net surplus of the network, taking into account the fixed-point conditions (exit).

Can solve for the sharing rules (λ_k are endogenously-determined).

The model generates three testable predictions:

1. Income is redistributed in favor of poor households within the caste.

2. Relatively wealthy households, who benefit less from the network, should be more likely to have migrant members.

*3. Households facing <u>greater</u> rural income-risk, who benefit more from the network, should be less likely to have migrant members.

Evidence on redistribution

Data: 2005-2011 Indian ICRISAT panel survey:

Household income over 7 years.

Consistent consumption data for 4 years.

Can characterize key moments from these data:

$$M_{Ik}, M_{Ak}, R_{Ik}, R_{Ak}$$

But too little permanent migration, not well-documented, and small sample size.

Table 5: Income and Consumption within the Caste

Data Source:	ICRISAT		
	relative income	relative consumption	consumption-income ratio
	(1)	(2)	(3)
Income class:			
1	0.119	0.460	3.871
2	0.281	0.625	2.224
3	0.373	0.626	1.680
4	0.510	0.673	1.319
5	1.000	1.000	1.000

2006 REDS Census is used:

119,000 households in 242 villages in 17 major states.

Permanent migration information is collected for every son/daughter of the head (whole household moves very rare).

But income is only available in the year prior to the survey.

Cannot compute the *M*'s or *R*'s.

Therefore average income and consumption and income variability are imputed using ICRISAT data (common soil variables, common India states, common rainfall characteristics, including rainfall variance).

Table 5: Income and Consumption within the Caste

Data Source:	REDS 2006			
	relative income	relative consumption	consumption-income ratio	migration
	(4)	(5)	(6)	(7)
Income class:				
1	0.316	0.843	2.665	0.032
2	0.416	0.854	2.052	0.034
3	0.513	0.871	1.697	0.051
4	0.627	0.887	1.413	0.046
5	1.000	1.000	1.000	0.051

Reduced-form tests

Proposition 1 indicates that relatively wealthy households in the caste are more likely to have migrant members.

Proposition 2 indicates that households facing greater rural income-risk should be less likely to have migrant members.

$$\mathrm{m_i} = \delta_0 + \delta_1 M_{iA} + \delta_2 M_{cA} + \delta_3 V_{iA} + e_i$$

where $\mathrm{m_i}$ = whether a male migrated permanently from the household in the previous 5 years; M_{iA} = household own average income, M_{cA} = average <u>caste</u> income, V_{iA} = household own variance in income.

$\delta_1 > 0$ (may be other reasons); $\delta_2 < 0$; $\delta_3 < 0$

Table 6
Relative Wealth within the Caste, Rural Income Risk and Permanent Male Migration

Variable	(1)	(2)	(3)	(4)
Household income	0.0059**	0.0051**	0.0026	0.0020
	(0.0024)	(0.0024)	(0.0045)	(0.0032)
Mean caste income, across all villages	-0.016***	-0.018***	-0.022**	-0.028***
	(0.0043)	(0.0055)	(0.010)	(0.0090)
Income risk	-	-0.00038***	-0.00037***	-0.00056***
		(0.00015)	(0.00013)	(0.00015)
Village mean income	-	-	0.007	-
			(0.013)	
Within-village mean caste income	-	-	-	0.0076
				(0.012)
N	19,362	19,362	19,362	19,362

Source: REDS Census, 2006

Structural estimates

The structural estimates are used to

A. Provide independent support for the redistribution within castes predicted by the theory (external validation).

B. Carry out counter-factual simulations

There are two exogenous variables in the model:

$$M_{Ak}; V_{Ak}$$

Within each caste *c* (100 in the listing data): $M_{Akc}; V_{Akc}$

Only two parameters to estimate!

β and v

assuming $F(\varepsilon) = 1 - e^{v\varepsilon}$

The exponential function satisfies the requirements for a unique equilibrium.

The model is solved to obtain the λ_k's for given β and v and the migration rates by income class, with no use of consumption data.

v is estimated in two steps:

1. Use REDS (rural income) and NSS (urban income) data to compute the average income-gain from migration for households with migrants, ε , and its utility-equivalent $\varepsilon^* = \log(1 + \varepsilon)$.

2. Use the percent of households with migrants, ρ, together with the properties of the exponential distribution, to derive

$$v = -\log(\rho/200)/\varepsilon^*$$

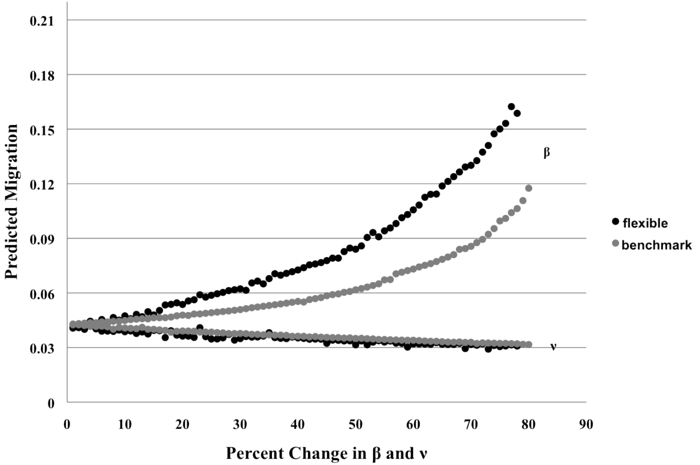
Can carry out within absolute income classes by caste.

Table 7
Comparison of Actual Relative Consumption and Migration with Structural Estimates, Based on Caste-Specific *v*'s

	Measured		Estimated	
Relative income class	Relative Consumption	Migration	Relative Consumption	Migration
1	0.843	0.032	0.730	0.032
2	0.854	0.034	0.744	0.032
3	0.871	0.051	0.765	0.046
4	0.887	0.046	0.825	0.044
5	1	0.051	1	0.051
β	-		0.991 (0.18)	

Source: REDS Census, 2006

Figure 6: Counter-Factual Simulation



Conclusion

Why does India have migration rates that are so much lower than comparable developing economies?

> Not that formal insurance is particularly weak in India.
>
> Not that informal insurance works particularly well there [high levels of risk-sharing have been documented throughout the developing world].

There is, however, more to consumption-smoothing than risk-sharing - covariate risk again!

The size, scope, and connectedness of caste networks may be exceptional.

Policy evaluations

Two counter-factual experiments are carried out with the estimated model:

1. Increased provision of formal credit, which always favor to wealthy households (collateral).

2. Government safety net for poor households.

Model enables examination of effects on migration by income class and on redistribution.

Figure 7: Reducing Risk in Higher Income-classes

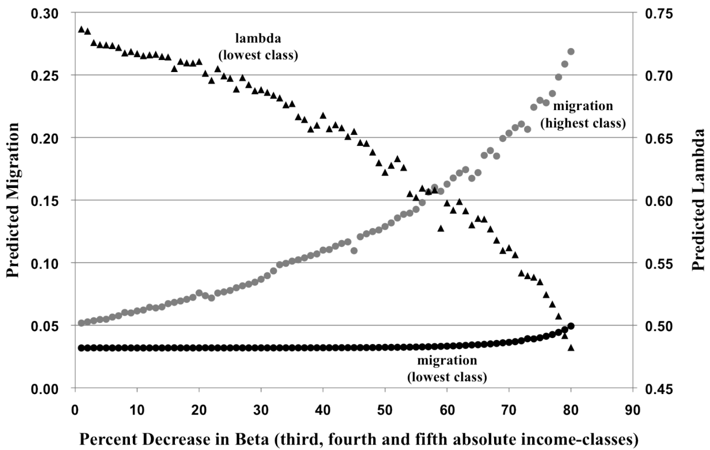
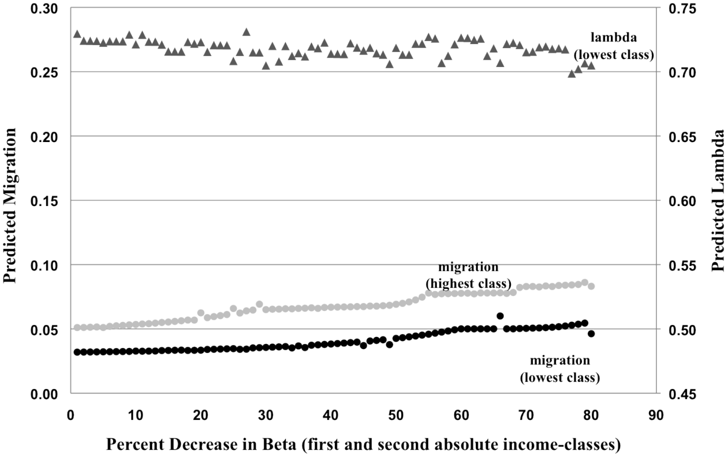


Figure 8: Reducing Risk in Lower Income-classes



Ex Post Temporary Migration and Network Risk-Sharing

Temporary migration is a mechanism that can smooth consumption.

In India, temporary, unlike permanent, migration is prevalent (30 million migrant workers).

A large component is *ex post* - out-migration from areas where realizations of adverse weather have occurred.

But networks also help smooth consumption.

What is the relationship between networks and temporary migration?

A. If migration opportunities increase, this makes the alternative to sharing risk in the network more attractive.

   This can reduce the ability of the network to smooth consumption.

B. Risk-sharing networks can make migration more attractive:

   If migration is risky, then risk-sharing makes migration less costly.

C. But, risk-sharing networks can make migration less attractive - since households are already smoothing consumption, the gain from migration is less.

How do we know what the relationship is? Morten (2017) paper

Model:

Both network risk-sharing and migration are endogenous.

Test the model:

Implications for consumption smoothing and migration.

Estimate the structure of the model:

Carry out counter-factual simulations:

Example: effects of an employment scheme on welfare, given endogenous migration and risk-sharing.

The Model

Standard model of a risk-sharing network with limited commitment, now with the addition of migration opportunities.

Two households with identical preferences.

There are draws of states s_t of nature each period at the village level, following a Markov process.

These village states of nature determine in each period the income of each household $e^i(s_t)$.

In the city there are iid stochastic events q_t that determine the income of any migrant $m^1(q_t)$ at time t.

Each period a households observes its draw of $e^i(s_t)$ and decides whether to send a temporary migrant to the city.

Temporary migration is thus strictly *ex post*.

There is a utility cost to migration $d(z)$, inclusive of transportation costs.

After-migration income is then a function of s_t, q_t, z.

Once incomes are realized for both households, there are risk-sharing transfers τ and consumption occurs for each.

Households cannot borrow or save (standard in these models).

The standard set up is that a social planner maximizes the utility of one household, say 2, given a state-dependent level of promised utility for household 1.

Here the social planner chooses migration, <u>after</u> the realization of s_t; transfers, after the realizations of q_t; and the continuation utility.

In the standard (no migration) limited commitment model, where a household can choose to renege on participating at any time and just consume its realized income (autarky), there is an additional *incentive-compatibility* constraint to ensure that a household does not quit.

With migration, there are two constraints.

A. "Before-migration constraint" (new), when the migration decision is made (and $e^i(s_t)$ is known):

> the expected value of following the planner's migration rule and staying in the network ≥ expected value of making its own decision and then forever being outside the network (autarky).

B. "After-migration" constraint, after migration outcomes are realized ($m^1(q_t)$ is also known):

> the value of following the planner's *ex post* risk-sharing transfer rule ≥ value of consuming all of the current income and then remaining independent (standard limited commitment constraint).

At any time t, the realized shocks will determine the distribution of village earnings F_E and the distribution of city earnings of the migrants $F_{M.}$

These will determine the distribution of consumption and earnings of each household.

define $$RS_t = \sigma_{cy}(F_E,F_{M,}d)/\sigma^2{}_y(F_E,F_{M,}d)$$

then

$$\mathrm{d}RS_t/\mathrm{d}d = \partial RS_t/\partial\sigma_{cy}[\partial\sigma_{cy}(F_E,F_{M,}d)/\partial d] + \partial RS_t/\partial\sigma^2{}_y[\partial\sigma^2{}_y(F_E,F_{M,}d)/\partial d]$$

How does a change in migration costs affect (a) the covariance of income and consumption and (b) the variance of income?

1. With lower migration costs, the independent option is more desirable, which reduces the return from participating in the network (the *ic* constraints bind more often), so σ_{cy} increases.

2. With lower d, can now more easily migrate out when the s_t are adverse. This facilitates transfers and would reduce σ_{cy}.

3. Migration could decrease the variance income (normalization) because households migrate when shocks are bad, or increase it (if city incomes are highly variable).

Welfare? If lowering d increases average incomes and reduces σ_{cy}, then welfare increases. But may not.

Need to estimate the model!

Data, Estimation and Findings

ICRISAT VLS 2001-2004 in the six original villages

Special module on temporary migration.

20% of households have at least one temporary migrant each year.

Little permanent migration (consistent with Munshi and Rosenzweig (2016)); temporary not a stepping stone.

Who are temporary migrants?

How do migrant households differ from other households?

Other facts:

A. Migration responds to *ex post* to rainfall shocks.

B. People move in and out of migration status: transition from temporary one year to staying next year = 40.2%.

C. Transfers appear to be insurance, and are consistent with a limited commitment model:

   Transfers are negatively affected by positive income shocks and by having more transfers in the past (history of shocks matter).

D. Households do not consume all of the income gain from migration - more evidence there is a transfer tax.

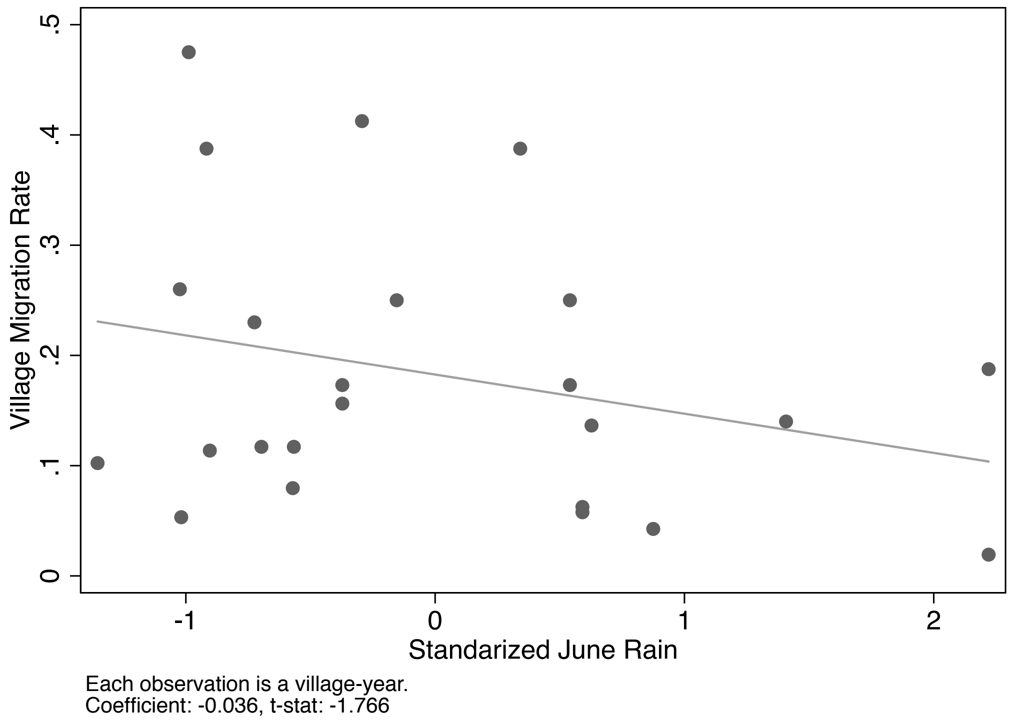


Figure 2: Verifying model assumptions: Temporary migration responds ex-post to income shocks.

Notes: The figure plots the relationship between the mean village migration rate and the standardized monsoon (June) rainfall in the six ICRISAT villages between 2001-2004. Monsoon rainfall is a strong predictor of crop income for the coming year. Migration decisions are made after the monsoon rainfall and respond to expected income shocks. The unit of observation is a village-year; there are 24 observations. A regression line is included in the figure.

Structural Estimates of the Model and Counter-Factuals

Main challenge is that a household's migration decision depends on the decision by all other households in the network.

Note: what is the relevant network?

Here the village is assumed to be the network (data size too small to divide into sub-caste groups).

This may be a problem, given prior findings.

Also, the model included only two households - but there are many in the village.

Construct "average rest of village" aggregate of income.

Structural estimates and findings using structural estimates:

1. Can estimate true gains from migrating - compare migrant income to counter-factual income would have had if stayed (not a comparison of stayers and movers)

   Why different? negative selectivity of migration.

2. Mean migration gain is positive, but 30% of migrants earn lower income than they would have made if stayed.

Counter-factuals:

Now can answer the comparative-statics questions.

1. Effect on risk sharing of reducing the cost of migration.

   By type of household, for households without migrants.

   Overall, improving access reduces risk sharing.

2. Effect of introducing risk-sharing on migration. Compare migration rates for three different risk-sharing regimes:

   A. Autarky - no risk sharing, borrowing or saving.

   B. Exogenous incomplete (selling and buying a risk free asset), independent of migration opportunities.

   C. Endogenous incomplete (limited-commitment model).

3. Effect of reducing the cost of migration on welfare under the three different risk-sharing regimes.

    Lowering migration costs lowers welfare in the presence of endogenous risk-sharing (limited commitment).

4. Policy: Effect of introducing a guaranteed employment scheme (NREGA) on migration and welfare under the three regimes.

    Introduced in 2005: 100 days at a statutory wage floor.

Table 7: Effect on risk sharing of reducing the cost of migration

	Whole sample		Only non-migrants	
	(1)	(2)	(3)	(4)
Risk sharing: corr(y, c)	No migration mean	With migration mean	No migration mean	With migration mean
Overall	0.064	0.198	0.059	0.195
Landless, few males	0.059	0.182	0.052	0.175
Landed, few males	0.066	0.194	0.061	0.190
Landless, many males	0.059	0.199	0.053	0.190
Landed, many males	0.066	0.207	0.064	0.205

Notes: Table compares risk sharing in an economy with the cost of migration very high so that noone migrates to the same economy with the cost of migration as estimated in the model. The risk sharing measure is the correlation between consumption and income. Columns 1 and 2 compute the statistic for the whole sample. Columns 3 and 4 compute the statistic only for households who don't migrate when they have the option: this keeps income constant. Risk sharing is crowded out by the increase in households' outside option with migration.

Table 8: Effect of reducing the cost of migration under different risk sharing regimes

	(1) Autarky	(2) Exogenous incomplete	(3) Endogenous incomplete
Migration rate			
Overall	0.416	0.260	0.166
Landless, few males	0.386	0.175	0.083
Landed, few males	0.333	0.139	0.068
Landless, many males	0.506	0.385	0.266
Landed, many males	0.440	0.341	0.248
Welfare gain relative to no migration			
Overall	1.126	1.080	0.923
Landless, few males	1.119	1.071	0.908
Landed, few males	1.090	1.053	0.913
Landless, many males	1.164	1.110	0.933
Landed, many males	1.129	1.086	0.937
Consumption equivalent gain relative to no migration			
Overall	0.220	0.160	-0.165
Landless, few males	0.195	0.133	-0.193
Landed, few males	0.160	0.106	-0.187
Landless, many males	0.284	0.218	-0.143
Landed, many males	0.239	0.182	-0.138

Notes: Table shows change in welfare with migration compared to no migration for whole sample and by subgroup. Endogenous incomplete markets is the limited commitment model. No risk sharing is autarky. Exogenous incomplete markets considers a Hugget (1993) economy where agents can buy and sell a risk-free asset.

Table 9: Effect of NREGA under different regimes

	Without migration			With migration		
	(1)	(2)	(3)	(4)	(5)	(6)
	Autarky	Exog	Endog	Autarky	Exog	Endog
Consumption equivalent gain with NREGA						
Overall	0.125	0.044	-0.016	0.029	0.011	0.058
Landless, few males	0.137	0.051	-0.015	0.034	0.013	0.063
Landless, many males	0.113	0.038	-0.016	0.030	0.011	0.060
Landed, few males	0.137	0.051	-0.015	0.029	0.011	0.056
Landed, many males	0.113	0.038	-0.016	0.025	0.009	0.054
Correlation between income and consumption with NREGA relative to pre-NREGA						
Overall			3.189			1.039
Landless, few males			3.192			1.088
Landless, many males			3.187			1.069
Landed, few males			3.192			0.998
Landed, many males			3.187			1.001
Migration rate with NREGA relative to pre-NREGA						
Overall				0.900	0.901	0.748
Landless, few males				0.800	0.850	0.791
Landless, many males				0.800	0.867	0.783
Landed, few males				1.000	0.947	0.735
Landed, many males				1.000	0.939	0.684

Notes: NREGA policy enacts an income floor in the village. The policy is computed allowing for migration and not allowing for migration. Endog. is limited commitment. Exog. is exogenously incomplete markets. Autarky is no risk-sharing.

Seasonal Migration and Urban Risk

A large proportion of temporary migration is seasonal - people migrate in anticipation of seasonally low demand <u>or</u> coming low harvest demand.

In Bangladesh, and in other countries, observe extreme temporary poverty in rural areas during the lean season and substantially higher wages in other areas in the same season.

Puzzle: why are there relatively low rates of seasonal migration?

> Maybe the returns are actually low - cannot assess returns by comparisons of stayers and people in other areas.
>
> If returns are high, what are the barriers to temporary moves?

Bryan *et al*. (2014) designed and carried out an RCT with a package of treatments, including direct incentives to migrate, during the lean season in a poor area of Bangladesh.

Monga lean season: between planting and harvesting.

Designed to:

A. Assess the true gains, if any, to migration.

B. To obtain a better understanding of the barriers to seasonal mobility:

riskiness of destination outcomes? liquidity? lack of information?

Experimental Design

"Vulnerable" (essentialy landless) households were target population in 100 villages.

Treatments in 2008, with follow-ups in late 2008, 2009, 2011:

1. Conditional cash transfer = $8.50 (37 villages)
2. Conditional credit (with limited liability) = $8.50 (31 villages)
3. Information/endorsement (16 villages)
4. Control (16 villages)

Results

A. Large response to the treatment:

   22 % point increase among households induced by the conditional cash/loan to send a migrant (36% of control hh’s had a migrant - low?).

B. Large real gains on average:

   Per-capita expenditures, food expenditures, calories increased by 30-35% in migrant households.

C. Risk of migration:

   1. 16% (28%) of control (treatment) group migrants earn < origin salary job (induced migrants less likely to have contacts at destination).

   2. Experimental provision of <u>destination</u> (Bogra) rainfall insurance increased migration for those previously incentivized to migrate to Bogra.

Thus, households are indeed risk-averse and perceive migration to be risky.

Puzzle: why such a large response to $8.50?

Model: focus on urban income riskiness - no rural risk!

Implications: households near subsistence less likely to migrate and more responsive to incentives (confirmed).

So,

A. Identifies very real large gains to migration and migration riskiness.

B. Still left with puzzle: why does a small amount of income induce a large migration response?

Implies large fluctuations in migration from year to year if just liquidity, or barriers to savings.

M^4 (2017): Migration Costs and Rural Risk Sharing

Uses the multiple-year data from Bryant *et al.* (2014) to examine the effect of inducing migration experimentally on risk sharing.

$$\log(C_{ivt}) = \gamma_{vt} + \alpha_0 \log(Y_{ivt}) + \alpha_1 \log(Y_{ivt}) \times T_v$$

where Y_{ivt} = origin income, T_v = treatment village

Find that $\alpha_1 < 0$ - lowering migration costs <u>increases</u> risk-sharing.

Why does this occur?

They formulate a limited commitment model of risk-sharing.

M^4 assume that rural incomes follow an AR1 process and estimate the parameters of the process.

> They allow the parameters to vary by treatment and control.

They show empirically that the treatment lowered the persistence, but not the variance, of rural incomes (net of migration income).

In the limited commitment model income predictability makes risk-sharing less attractive.

Lowering origin-income persistence thus relaxes the constraints on risk-taking.

This result raises the question of why migration should alter the properties of the rural income process.

Potential mechanisms, not modeled:

A. General-equilibrium effects of increased migration on supply of labor alter production practices.

B. Risk portfolio adjustments: change risk profile of enterprises given lower costs of *ex post* migration (better ability to consumption smooth allows more risk -taking, e.g., crop choice (Rosenzweig and Binswanger, 1993)).

In all these studies rural income properties are exogenous; too little attention to the demand side and production decisions.

Rural Risk, *Ex Post* and Anticipatory Migration: Equilibrium Effects

Limitations of prior studies on migration and rural risk:

A. Origin income variability is assumed to be exogenous.

   But farmers choose seeds and technologies that differ in their sensitivity to rainfall.

B. There are no general-equilibrium effects of migration.

   If temporary migration is prevalent, then variation in migration will affect stayers' (origin) incomes.

   Migration smooths the incomes of stayers, without τ.

C. Migration only occurs after the realization of the shock *(ex post*) or in anticipation of low demand, not both.

D. Sequential nature of agricultural production not modeled.

Rosenzweig and Udry (2017):

Construct a dynamic, equilibrium model:

Farmers choose how much to invest and how much risk to take *ex ante*.

Landless decide on migration before (*ex ante*) and after *(ex post*) shocks occur.

Examine effects of rainfall forecasts, minimum wages on

Farmer investments and risk-taking prior to realized rainfall.

Anticipatory, before, and *ex post* migration.

Profits, after rainfall.

Equilibrium wages before and after the rainfall occurs.

India data:	ICRISAT 2009-2015.
	NSS, various rounds.
	REDS, ARIS.

The focus on forecasts is for three reasons:

1. Improving forecasts is a promising means of increasing farmer incomes - risk is reduced and farmers can exploit predictable weather outcomes to enhance profits and reduce profit variability.

   Superior to weather insurance: just makes farmers' indifferent to risk, zero marginal cost of adding a client.

2. Forecasts only affect behavior by altering expectations; thus information on how variation in forecasts affect behavior and outcomes can be used to more precisely test the dynamic model.

3. Having public forecasts is desirable in empirical analyses of general-equilibrium models:

    A. They are orthogonal to agent characteristics.

    B. They are released prior to the resolution of uncertainty by definition.

    C. They affect all agents simultaneously.

There are forecasts: the Indian Metereological Department (IMD) long-range forecasts of July-September (*Kharif* season) monsoon rainfall are issued at the end of June every year. We use them to both test the model and to evaluate their effects:

A. On farmer investments and risk-taking.

B. On farmer profits.

C. On migration decisions - *ex ante* (anticipatory) and *ex post*.

D. On planting-stage and harvest-stage wages.

First quantitative assessment of improving forecasting skill in terms of the incomes of both the landless and landed.

It is obvious that a forecast of good weather, if believed, will lead to changing investment behavior by farmers.

But the data indicate that workers respond as well, via migration.

Most of the literature on temporary migration has focused on:

A. Migration in the off-season, when agricultural work is at a low level.

B. Migration in response to weather shocks - *ex post* migration, at harvest time.

But there is also a peak of migration at planting time, and this varies across years.

Figure 1. Proportion of Rural Migrant Workers Among Men Aged 19-49, by Month (Source: ICRISAT VLS 2010-2014)

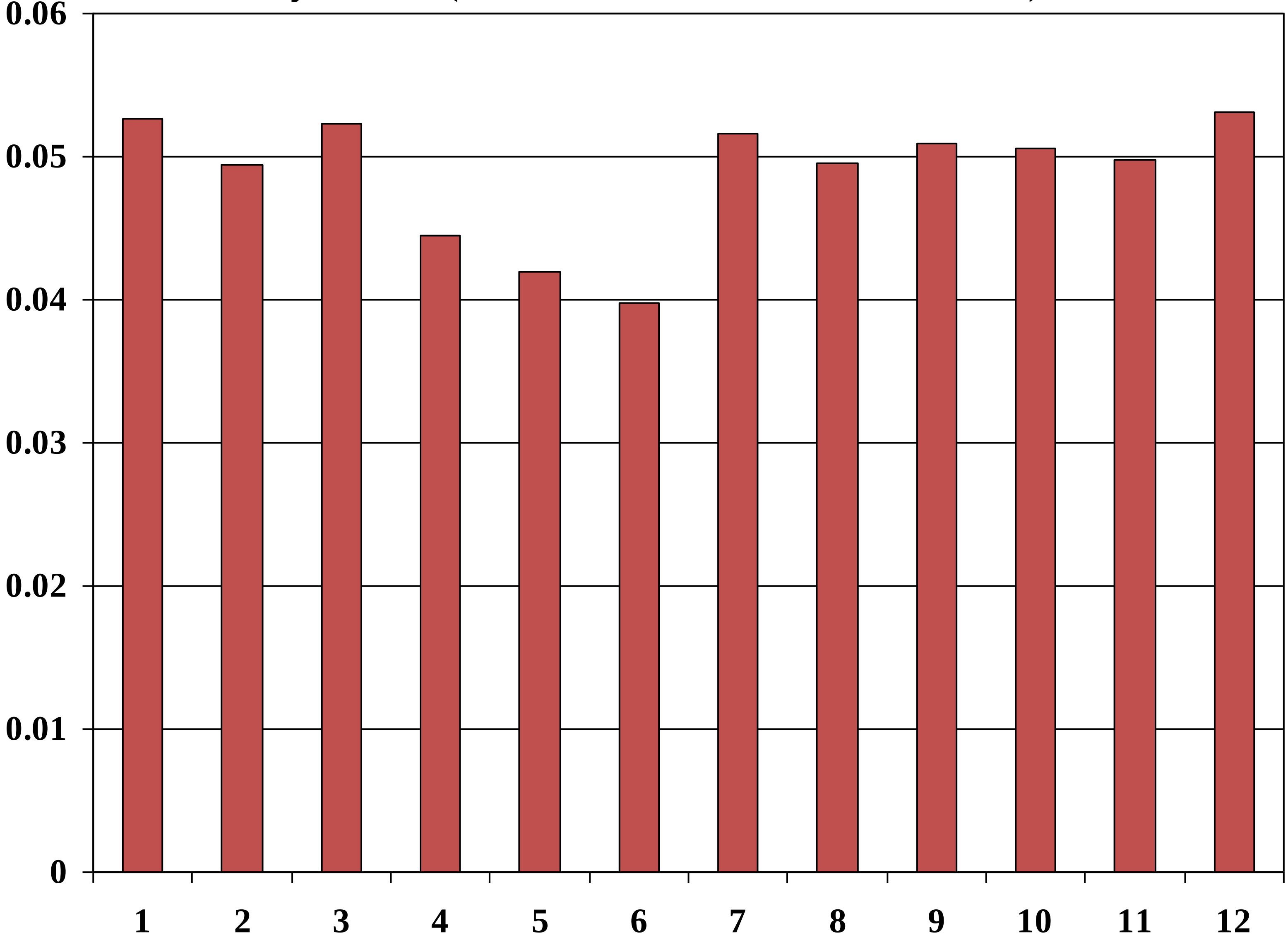


Figure 2. Proportion of Rural Workers in Urban Areas Among Men Aged 19-49, by Month (Source: ICRISAT VLS 2010-2014)

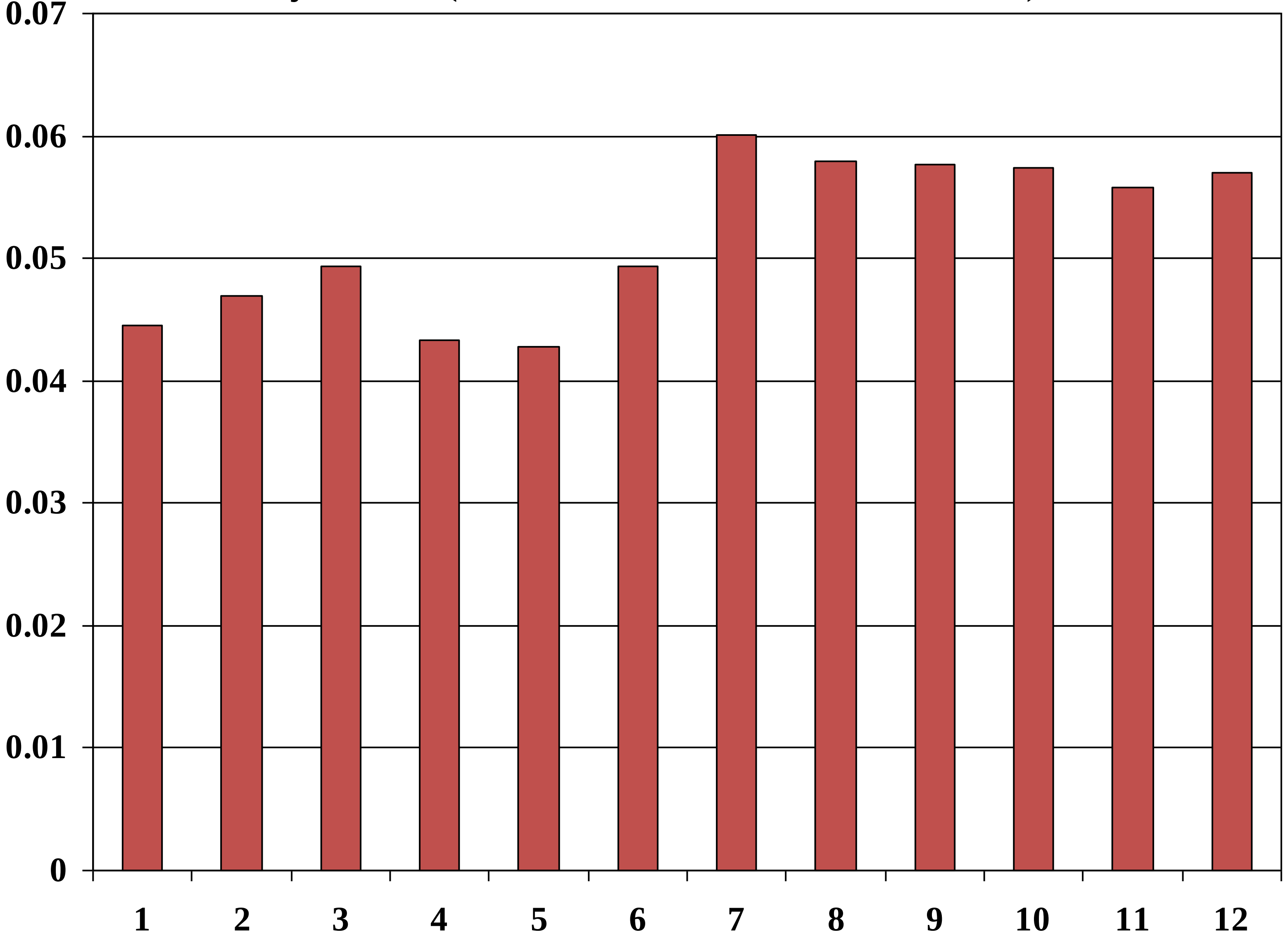


Figure 3. Proportion of Rural Workers Away from Home Among Men Aged 19-49, by Month (Source: NSS Round 66, 2009/10)

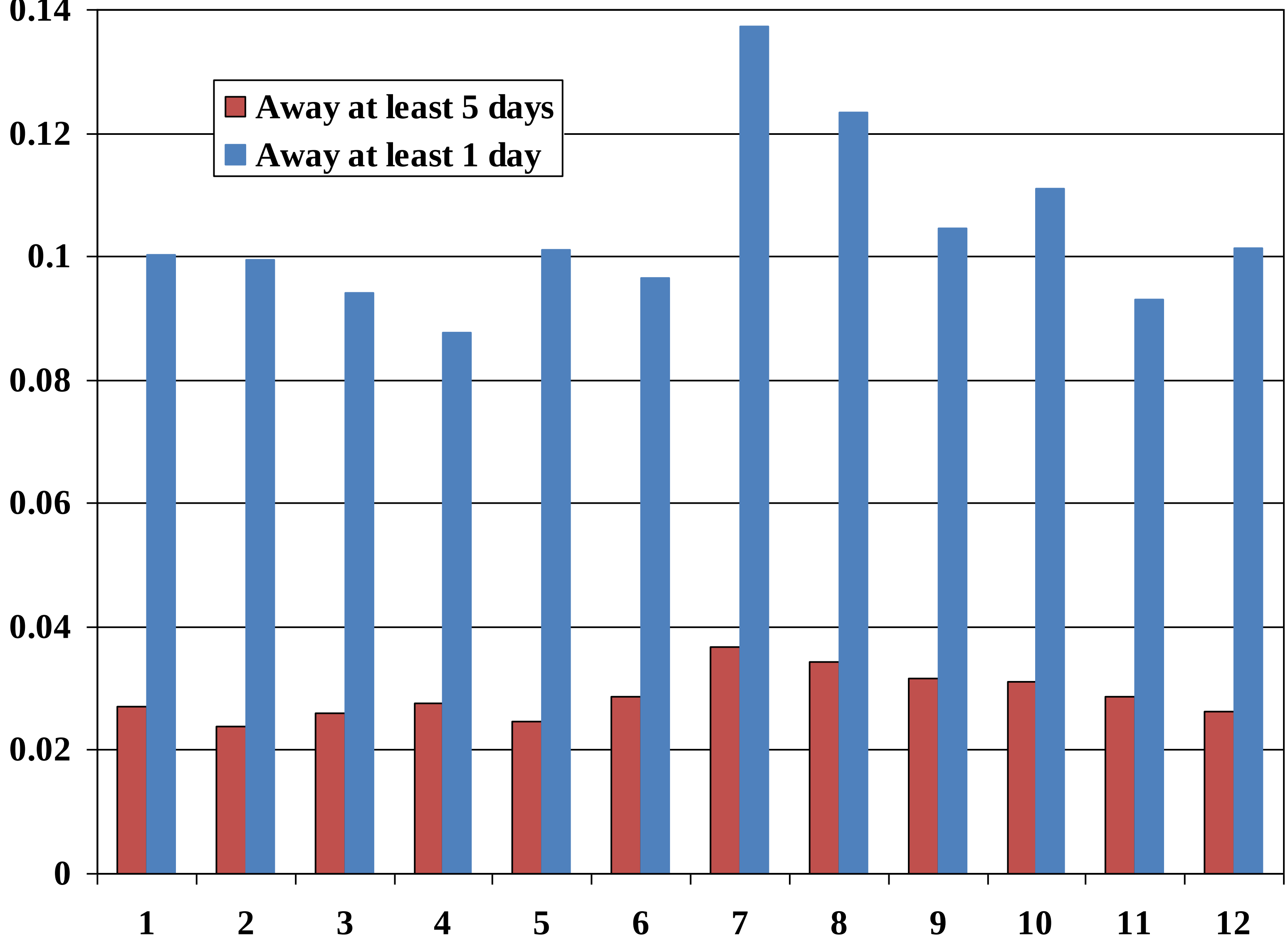


Figure 4. Proportion of Migrant Workers Among Men Aged 19-49 in July, by Year (Source: ICRISAT VLS 2010-2014)

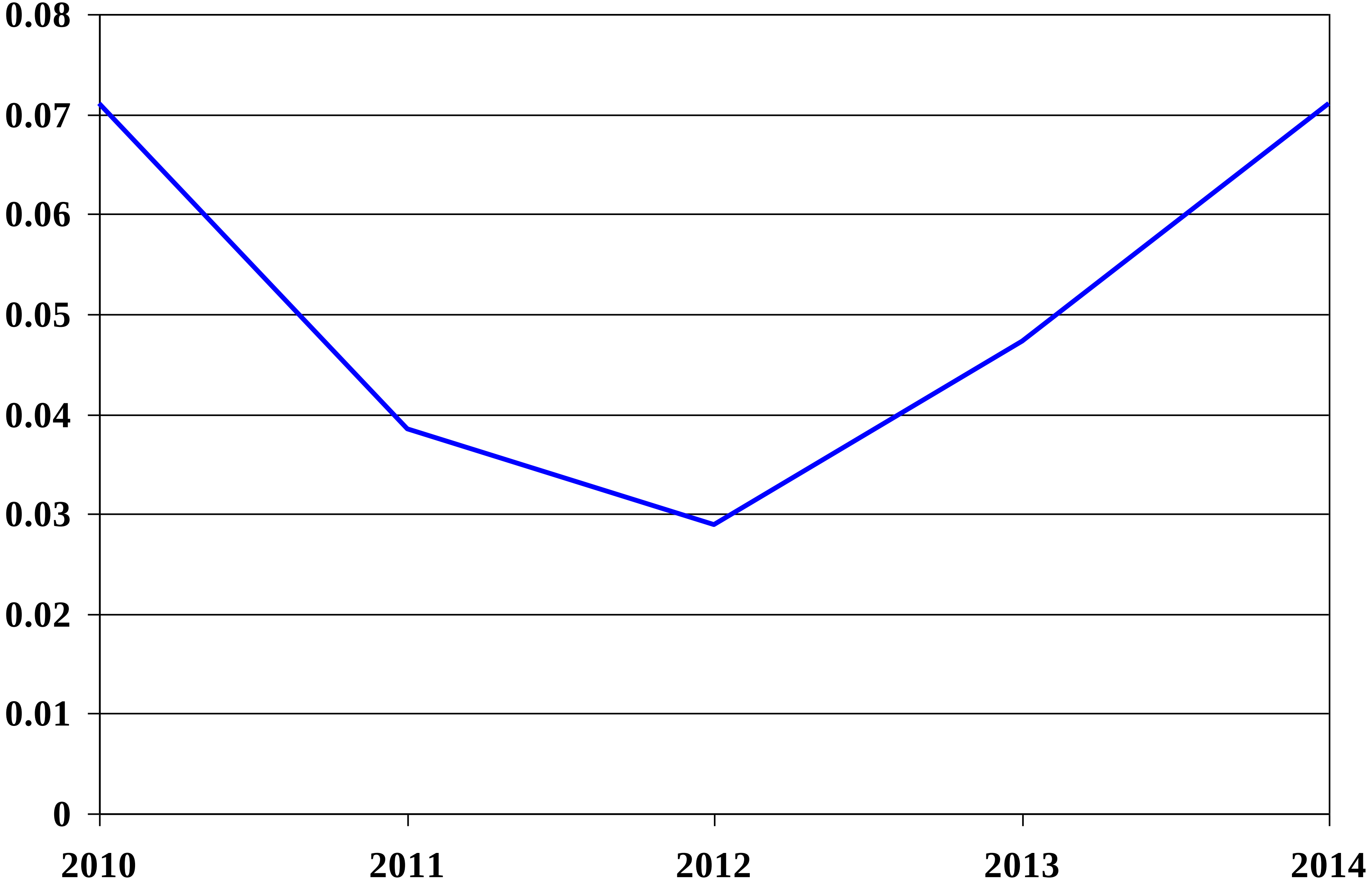
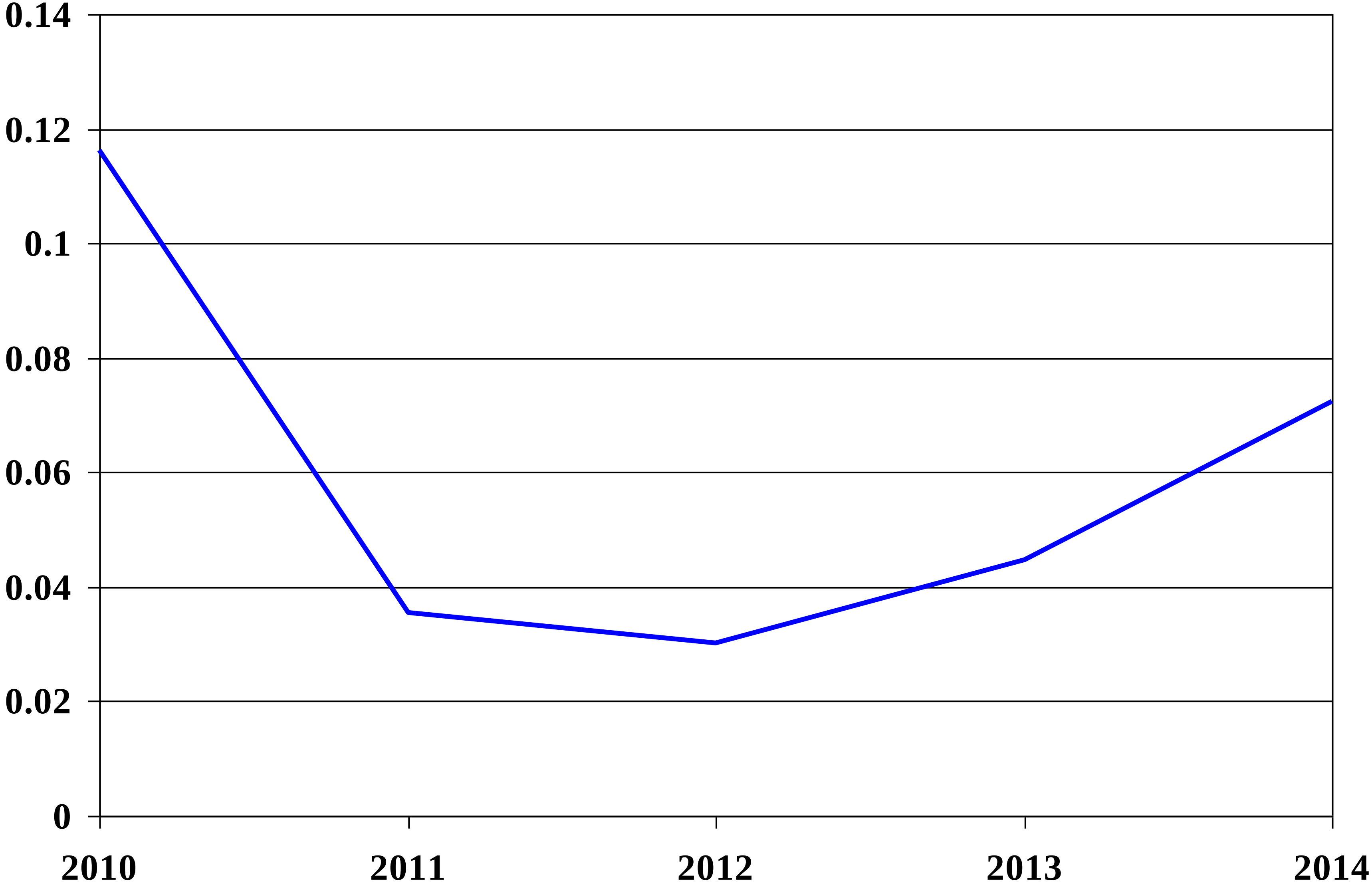


Figure 5. Proportion of Workers Among Men Aged 19-49 in Urban Areas in July, by Year (Source: ICRISAT VLS 2010-2014)



[Variation in planting-stage migration could be due to demand fluctuations other than via forecast variation (liquidity, moisture overhang from prior rainfall outcomes).]

Key point: the effects of any forecast (or other policy change) will depend on anticipatory migration responses.

A forecast of bad weather is *likely* to induce farmers to invest less, so one would expect planting-stage wages to be lower.

This ignores a migration response: rational workers will migrate out in response to lower demand at the planting stage and in anticipation of a lower wage at the harvest stage.

The effect on the equilibrium agricultural wage is not obvious.

The model is also used to evaluate the effect of guaranteed employment schemes.

- These programs guarantee employment at a minimum wage.

- Most of the focus of such schemes is on how they aid workers during slack times - such as at harvest times when rainfall has been low.

But, the anticipation of a higher minimum wage that could bind at harvest, due to poor weather, will affect migration at the planting-stage.

And minimum wage rate changes interact with the forecasts.

In India, the statutory minimum wage is increased periodically, and varies across states:

From 2005-2012, as many as 7 times in some states.

And, inflation will affect the level of real wage floors in the absence of statutory changes.

Of course, the variation in minimum wages, set by politicians, is not as pristine as the variation in forecasts, which presumably are the outcomes solely of science-based weather models.

The Model

Environment

- Two periods: 1. Planting 2. Harvest
- Two possible states realized in harvest: $s \in \{b, g\}$
- Forecast released before period 1: $F \in \{B, G\}$
- Forecast skill: $q = prob(s = b|F = B) = prob(s = g|F = G)$

Preferences

- Subscripts denote period/realized state, and forecast:

  c_{1F} - period 1, after forecast F;

  c_{sF} - period 2, state s after forecast F

- Everyone has CRRA preferences:

$$\frac{1}{1-\gamma}\left[c_{1F}^{1-\gamma} + prob(S=b|F)c_{bF}^{1-\gamma} + prob(S=g|F)c_{gF}^{1-\gamma}\right]$$

Cultivators

- Use labor at planting (x_{1F}) and harvest (x_{sF}).
- Technology choice at planting $R \in [0,1]$

$$Q_{bF} = x_{1F}^{\beta}(1-R)$$
$$Q_{gF} = \theta x_{1F}^{\beta}(1+R)$$

- Harvest period labor demand linear

$$x_{sF} = Q_{sF}$$

- No alternative savings, credit or insurance

$$c_{1F} = Y_c - w_{1F}x_{1F}$$
$$c_{sF} = Q_{sF}(1-w_{sF})$$

Landless

- Supply labor locally, or migrate seasonally (*m*=1)
- Harvest season: $c_{sF} = \max(w_{2u}, w_{sF})$
- Planting season:
  $$c_{1F} = I(m = 1)w_{1u} + \big(1 - I(m = 1)\big)w_{1F} + Y_l$$
- Urban wages randomly drawn indep for each worker
  - Planting season: drawn from $F_1(w)$
  - Harvest season
    - If migrated in planting season: drawn from $F_2(w)$
    - If stayed in village in planting season: drawn from $F_1(w)$
  - $F_2(w)$ f.o.s.d. $F_1(w)$

Technology choice

- Given a forecast F and equilibrium wage vector (w_{1F}, w_{gF}, w_{bF}), farmer chooses x_{1F} and R_F

- If $F = G$,

$$\frac{1+R_G}{1-R_G} = \left(\frac{q}{(1-q)}\right)^{\frac{1}{\gamma}} \left(\frac{\theta\left(1-w_{gG}\right)}{(1-w_{bG})}\right)^{\frac{1}{\gamma}-1}$$

Analogous condition for forecast of B.

Risk-taking increases with the likelihood of good weather, and (iff $\gamma < 1$) with the net income in good weather vs bad weather

Labor Supply

- Given a forecast F, an equilibrium wage vector (w_{1F}, w_{gF}, w_{bF}), and a draw w_{1u} from $F_1(w)$, a landless worker chooses planting season migration $m_{1F} = \{0,1\}$
- Trigger wage strategy

$$m_{1F} = 1 \text{ iff } w_{1u} \geq w_{mF}^*$$

- Option value of $F_2(w)$ implies $w_{mF}^* < w_{1F}$

$$\frac{dw_{mF}^*}{dw_{1F}}, \frac{dw_{mF}^*}{dw_{sF}} > 0$$

Labor Supply

- Village labor supply in planting season after F

$$S_{1F} = F_1(w^*_{mF})$$

- Village labor supply at harvest in s after F

$$S_{sF} = S_{1F}F_1(w_{sF}) + (1 - S_1)F_2(w_{sF})$$

Labor Market Equilibrium

- After forecast F, equilibrium defined by $\{w_{1F}, w_{gF}, w_{bF}\} \equiv \boldsymbol{w_F}$ s.t

$$F_1\left(w^*_{mF}(\boldsymbol{w_F}, F)\right) = S_1 = x_{1F}(\boldsymbol{w_F})$$

$$S_1 F_1(w_{bF}) + (1 - S_1) F_2(w_{bF}) = x_b\left(x_{1F}(\boldsymbol{w_F}), R_F(\boldsymbol{w_F})\right)$$

$$S_1 F_1\left(w_{gF}\right) + (1 - S_1) F_2(w_{gF}) = x_g\left(x_{1F}(\boldsymbol{w_F}), R_F(\boldsymbol{w_F})\right)$$

Implications of Observable Patterns of Investment and Profits

$$\omega_G \equiv \frac{1 - w_{bG}}{1 - w_{gG}}$$

Empirical Regularity	$\pi_{gG} > \pi_{bG}$	$\pi_{gG} < \pi_{bG}$
$x_{1G} - x_{1B} > 0$ $\mathrm{R}_G - \mathrm{R}_B > 0$	$\gamma < 1$ $\frac{\theta(1 + R_G)}{1 - R_G} > \omega_G$	$\gamma > 1$ $\frac{\theta(1 + R_G)}{1 - R_G} < \omega_G$
$x_{1G} - x_{1B} < 0$ $\mathrm{R}_G - \mathrm{R}_B$	$\gamma > 1$ $\frac{\theta(1 + R_G)}{1 - R_G} > \omega_G$	$\gamma < 1$ $\frac{\theta(1 + R_G)}{1 - R_G} < \omega_G$

Implications of Observable Patterns of Investment and Profits

$$\omega_G \equiv \frac{1 - w_{bG}}{1 - w_{gG}}$$

Empirical Regularity	$\pi_{gG} > \pi_{bG}$	$\pi_{gG} < \pi_{bG}$
$x_{1G} - x_{1B} > 0$ $\mathrm{R}_G - \mathrm{R}_B > 0$	$\gamma < 1$ $\frac{\theta(1 + R_G)}{1 - R_G} > \omega_G$	$\gamma > 1$ $\frac{\theta(1 + R_G)}{1 - R_G} < \omega_G$
$x_{1G} - x_{1B} < 0$ $\mathrm{R}_G - \mathrm{R}_B$	$\gamma > 1$ $\frac{\theta(1 + R_G)}{1 - R_G} > \omega_G$	$\gamma < 1$ $\frac{\theta(1 + R_G)}{1 - R_G} < \omega_G$

Empirical Implications – Planting Season

Observable outcome	**Change with respect to**	
	Forecast	increased skill
Risk-taking	$R_G - R_B > 0$	$\frac{dR_G}{dq} > 0$
Planting investment	$x_{1G} - x_{1B} > 0$	$\frac{dx_{1G}}{dq} > 0$
Planting season wages	$w_{1G} - w_{1B} =?$	$\frac{dw_{1G}}{dq} =?$
Planting season migration	$1 - S_{1G} < 1 - S_{1B}$	$\frac{d(1 - S_{1G})}{dq} < 0$

Empirical Implications – Harvest

observable outcome	Change with respect to		
	Forecast	increased skill	rainfall realization
Harvest season wages	$w_{sG} - w_{sB}$ $=?$	$\frac{dw_{sG}}{dq} =?$	$w_{gF} - w_{bF}$ > 0
Harvest season migration			$1 - S_{gF}$ $< 1 - S_{bF}$

Empirical Implications – Harvest

Interactions of forecasts and weather realizations	
$\frac{1-S_{gG}}{1-S_{bG}} < \frac{1-S_{gB}}{1-S_{bB}}$	$\frac{d\left(\frac{1-S_{gG}}{1-S_{bG}}\right)}{dq} < 0$
$\frac{\pi_{gG}}{\pi_{bG}} > \frac{\pi_{gB}}{\pi_{bB}}$	$\frac{d\left(\frac{\pi_{gG}}{\pi_{bG}}\right)}{dq} > 0$
$\frac{w_{gG}}{w_{bG}} > \frac{w_{gB}}{w_{bB}}$	$\frac{d\left(\frac{w_{gG}}{w_{bG}}\right)}{dq} > 0$

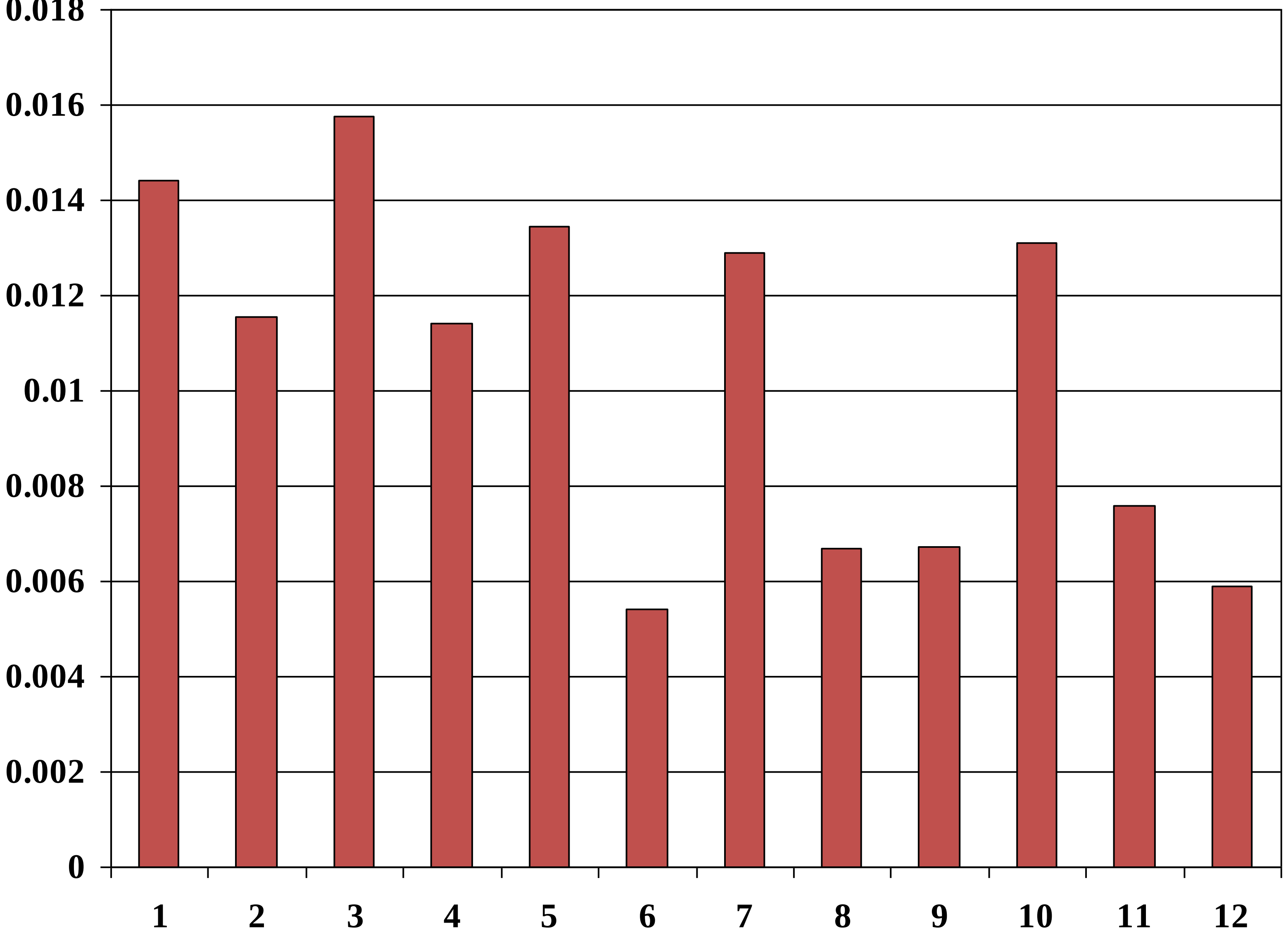
Minimum Wages – Planting Season

- Rural employment schemes generate wage floors that may bind seasonally.
- Suppose w_m binds *in planting* after $F = B$
- Equilibrium defined with $\{w_{gB}, w_{bB}\}$ such that $\{w_m, w_{gB}, w_{bB}\} \equiv \boldsymbol{w_B}$ solves

$$w_{gB}\left(S_{1B}(\boldsymbol{w_B})f_1 + \left(1 - S_{1B}(\boldsymbol{w}_B)\right)f_2\right)$$
$$= \theta\left(1 + R_G(\omega_{gB})\right)\left(x_B^0(\boldsymbol{w_B})\right)^{\beta}$$

$$\frac{w_{gF}}{w_{bF}}\left(\frac{1 - w_{bF}}{1 - w_{gF}}\right)^{1-\frac{1}{\gamma}} = \theta^{\frac{1}{\gamma}}\left(\frac{q}{(1-q)}\right)^{\frac{-1}{\gamma}}$$

Figure 6. Proportion of Rural Workers Employed in Public Works Programs Among Men Aged 19-49, by Month (Source: NSS Round 66, 2009/10)



Typology of binding wage floors

Floor binds at	w_{1B}	w_{bG}	w_{gG}	w_{bB}	w_{gB}
Never	w_{1B}	w_{bG}	w_{gG}	w_{bB}	w_{gB}
Planting $F = B$	$\tilde{w}_{1B} = w_{min}$	$\tilde{w}_{bG} = w_{bG}$	$\tilde{w}_{gG} = w_{gG}$	$\tilde{w}_{bB} < w_{bB}$	$\tilde{w}_{gB} < w_{gB}$
Harvest (bG)	$\tilde{w}_{1B} < w_{1B}$	$\tilde{w}_{bG} = w_{min}$	$\tilde{w}_{gG} < w_{gG}$	$\tilde{w}_{bB} = w_{bB}$	$\tilde{w}_{gB} = w_{gB}$
Harvest (bB)	$\tilde{w}_{1B} < w_{1B}$	$\tilde{w}_{bG} = w_{bG}$	$\tilde{w}_{gG} = w_{gG}$	$\tilde{w}_{bB} = w_{min}$	$\tilde{w}_{gB} < w_{gB}$
Planting + Harvest (bB)	$\tilde{w}_{1B} = w_{min}$	$\tilde{w}_{bG} = w_{bG}$	$\tilde{w}_{gG} = w_{gG}$	$\tilde{w}_{bB} = w_{min}$	$\tilde{w}_{gB} < w_{gB}$

Typology of binding wage floors

Floor binds at	$M_G = (1 - S_G)$	M_B	R_G	R_B
Never	M_G	M_B	R_G	R_B
Planting $F = B$	$\widetilde{M}_G = M_G$	$\widetilde{M}_B < M_B$	$\tilde{R}_B = R_B$	$\tilde{R}_B < R_B$
Harvest (bG)	$\widetilde{M}_G < M_G$	$\widetilde{M}_B = M_B$	$\tilde{R}_B < R_B$	$\tilde{R}_B = R_B$
Harvest (bB)	$\widetilde{M}_G = M_G$	$\widetilde{M}_B < M_B$	$\tilde{R}_B = R_B$	$\tilde{R}_B < R_B$
Planting + Harvest (bB)	$\widetilde{M}_G = M_G$	$\widetilde{M}_B < M_B$	$\tilde{R}_B = R_B$	$\tilde{R}_B < R_B$

The Data Sets

Four panel data sets are used:

A. The ICRISAT Village Dynamics in South Asia (VDSA) 2009-2014

1. 18 villages located in the states of Andhra Pradesh, Gujarat, Karnataka, Maharashtra, and Madhya Pradesh.

2. Panel of (landless and landed) individuals (2,000 prime age adults) and farms (650).

3. Information on inputs and outputs collected at high frequency over the crop year (every three weeks)

4. Information on daily rainfall for each village in survey years and prior years (long time-series for some villages).

5. Information on temporary migration and wages *by month*.

B. 1999 and 2007-8 Rural Economic and Development Surveys (REDS)

1. Carried out by the National Council of Economic Research in 242 villages in 100 districts in the 17 major states of India (not Assam, J&K).

2. Agricultural inputs collected by stage and season.

3. Information on monthly rainfall by village for each year between 1999-2007.

   Can assess IMD forecast skill by at the village level across India (July-September rain).

   Can estimate the response of farmer investments to forecast by forecast skill.

   2,219 farmers (4,438 observations) in 212 villages and 100 districts

C. 1968-71 Additional Rural Income Survey (ARIS)

1. 3-year panel of 2600 farmers.

2. Same national set of villages as REDS.

3. Information by village on “adverse” rainfall in each year.

4. Can compute profits.

   Survey taken at the onset of the “green revolution,” so can examine risk-taking in the form of new technology adoption (HYV seeds).

D. National Social Survey (NSS): National panel at the district or sub-district level

1. NSS Schedule 1.0 provides information on days away from home in last month - temporary migration.

   Information is collected in different month, so migration available *by month*.

   We use rounds 62, 63, 64, 66: 2005-2007 and 2009.

   Up to 25,000 prime age adults in a round.

   No rainfall information: use TRMM satellite data matched to villages.

2. NSS Schedule 10.0 provides information on daily wages.

Available *by month*: observe monthly patterns of wages

We use rounds 61, 63, 68: 2004, 2009, 2011

Up to 165,000 prime-age adults in a round.

IMD Monsoon Forecasts and Forecast Skill

The Indian Meteorological Department (IMD) in Pune issues at the end of June forecasts of July-September rainfall (summer monsoon)

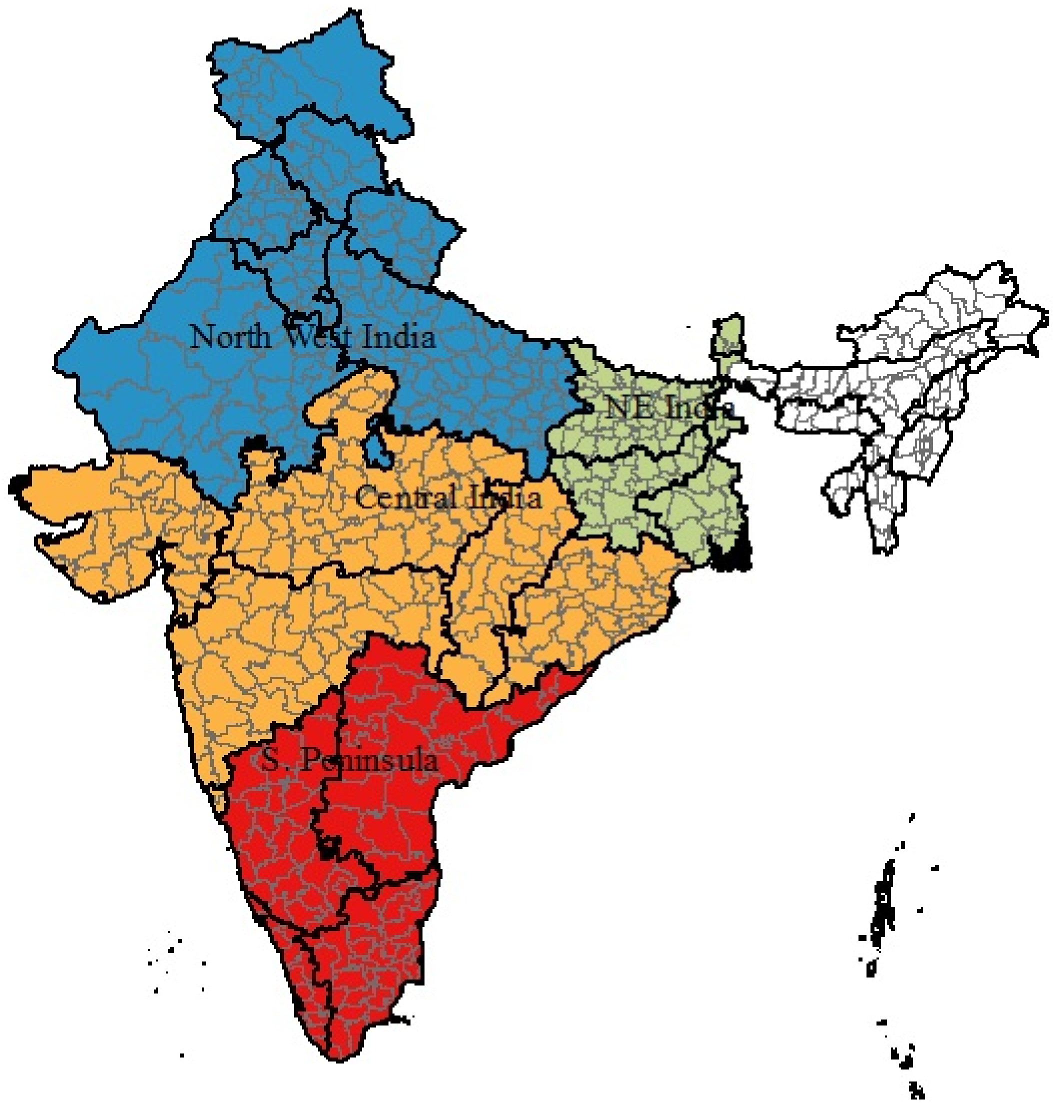
July-September rainfall accounts for70% of rainfall over the whole crop year.

Critical for *kharif*-season profitability (planting in June-August)

IMD established in 1886 and has been issuing these forecasts annually since then

Appendix Map A1

India Meteorological Department



For 1999-2010, using IMD published data, we find that:

A. Forecast skill is not high.

B. Symmetry property assumed in the model holds:

   Whether a below- or above-normal forecast, slightly greater than 50% chance the forecast is correct.

C. But, forecast skill varies by region, and for some areas of India the forecast has skill.

   1999-2003: forecasts issued for three regions

   2004-2010: forecasts issued for four regions (Map A)

We obtained the correlations between the relevant regional forecasts and the actual (July-September) rainfall time-series in the ICRISAT and REDS (national) villages.

These data provide on-the-ground observations of rainfall at the village level, not interpolations.

ICRISAT: Table 2: Forecast skill by village, for the original six ICRISAT villages, 2005-2011

A. For the Maharashtra villages, skill is relatively high (ρ =.267)

B. For the Andhra Pradesh villages, worthless (not due to CV).

REDS: Map 1: shows based on the 212 REDS villages (1999-2006), the districts where the forecast has skill.

A. Overall correlation is .132, ranging from .01 to .77.

B. See there are broad contiguous geographical regions where the skill is higher.

Why does skill differ?

Rainfall distribution characteristics vary spatially and are imperfectly correlated.

Rainfall in area *i* does not predict well rainfall in *j*.

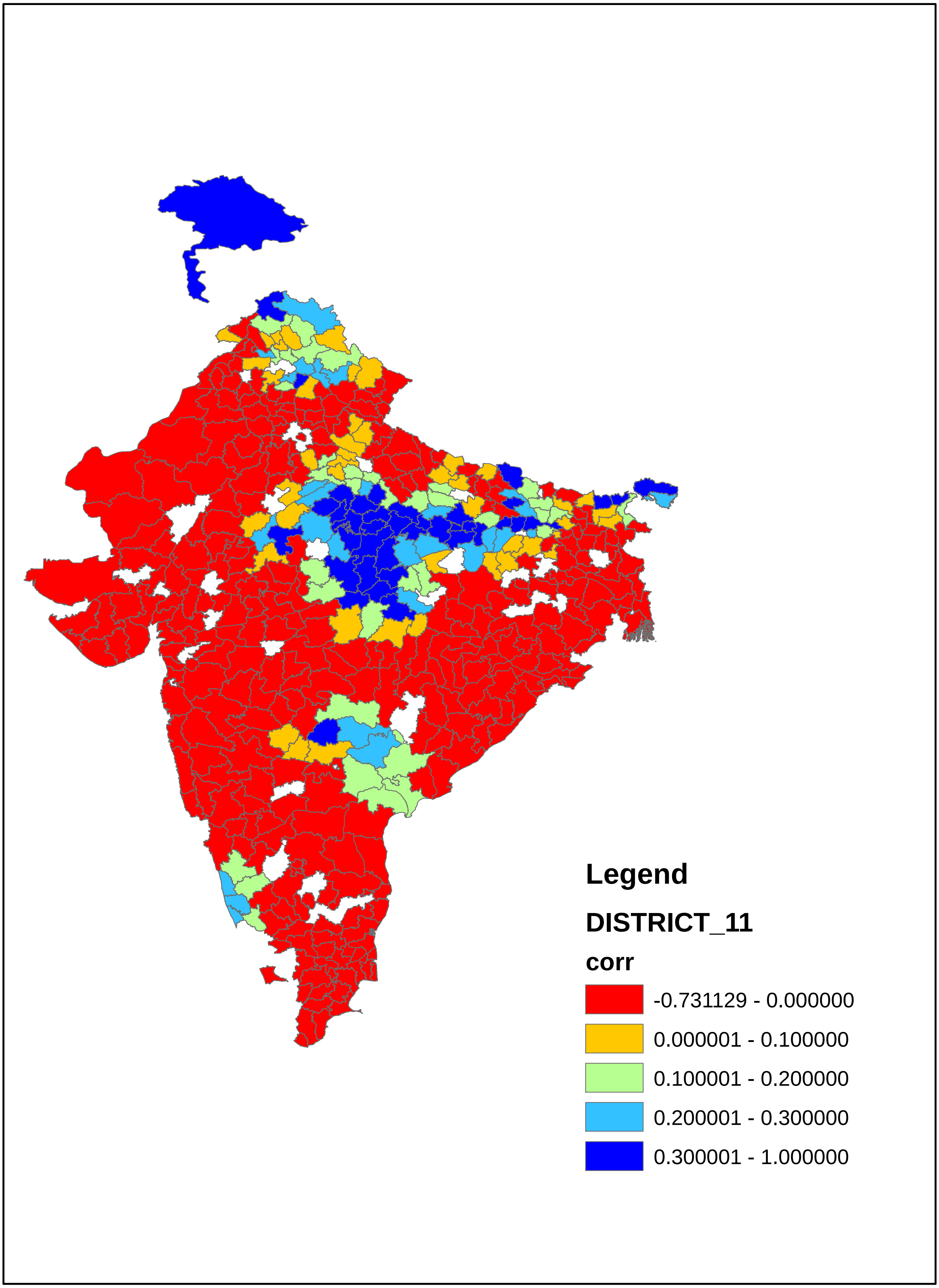
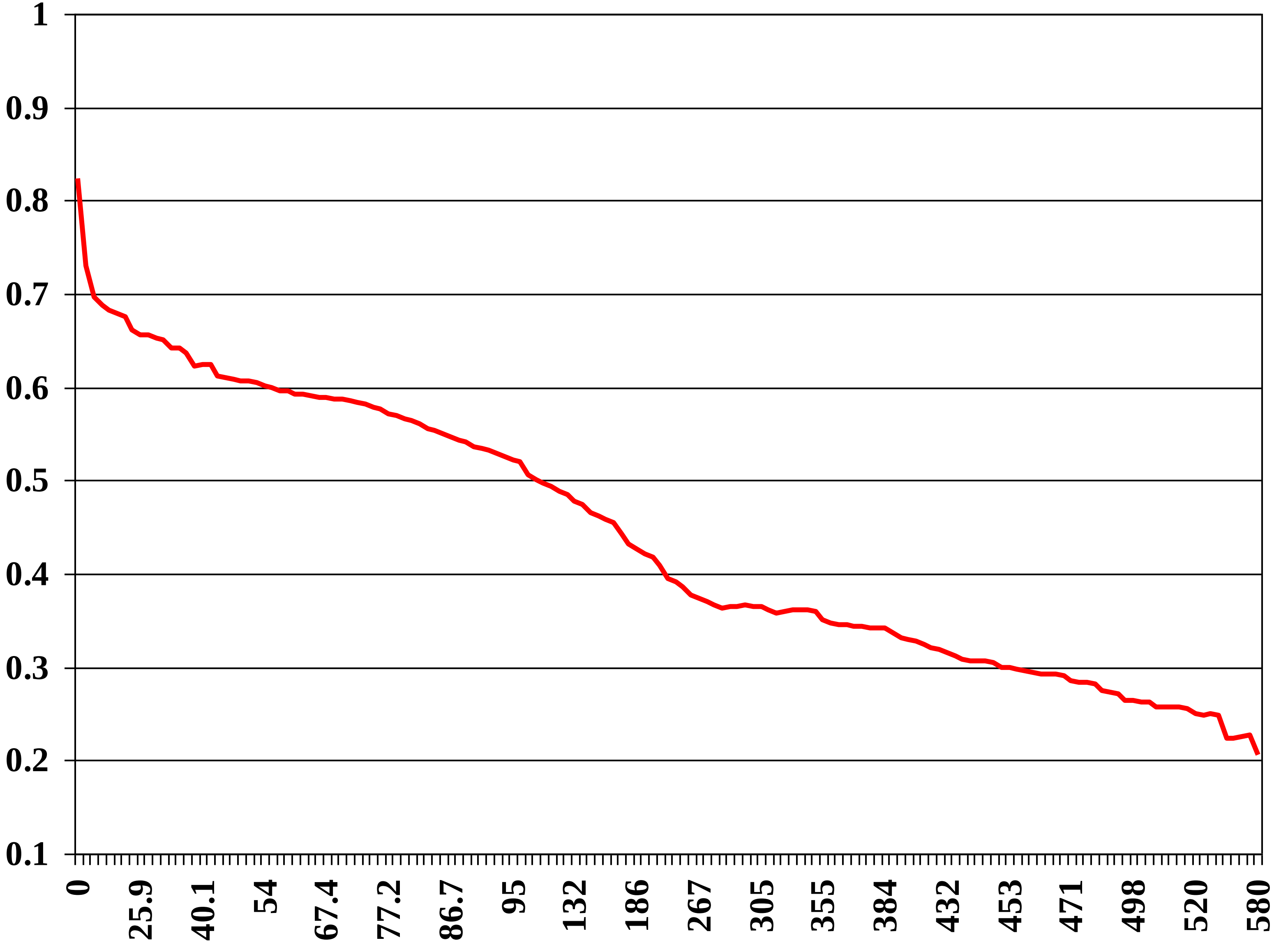

Legend
DISTRICT_11
corr
-0.731129 - 0.000000
0.000001 - 0.100000
0.100001 - 0.200000
0.200001 - 0.300000
0.300001 - 1.000000

Figure A: Lowess-Smoothed Relationship between Inter-Village Distance (Km) and June-August Rainfall Correlation, Andhra Pradesh and Uttar Pradesh 1999-2007



Tests of the Model

We first assess what quadrant of the model we are in: is $\gamma < 1$?

Does a forecast of good weather increase planting-stage investment ($x_{1G} - x_{1B} > 0$)?

Is the response greater if the forecast has more skill?

Do profits increase with good weather?

Do profits increase more in good(bad) weather when there is a good(bad)-weather forecast?

The payoff for farmers from forecasting.

We then look at planting-stage behavior:

Risk-taking responses to the forecast (demand):

$$R_G - R_B > 0?$$

Planting-stage migration responses to the forecast (supply):

$$1 - S_{1G} - 1 - S_{1B} < 0?$$

Is anticipatory migration in the planting affected by the forecast?

Key: What is the equilibrium planting-stage wage response to the forecast?

What happens to planting-stage wages is the initial payoff for wage workers from forecast.

Theoretically ambiguous:

If the planting-stage migration response is sufficiently strong may see that $w_{1G} < w_{1B}$.

Stayers worse off when the forecast is good.

But, worker welfare is improved from more accurate forecast, just more wage volatility.

Table 3
Farmer Fixed-Effect Estimate of the IMD Forecast Effect
on *Kharif*-Season Log Planting-Stage Investment
ICRISAT Villages with Skill, 2009-2014

Variable	(1)	(2)
Forecast<98	-0.0605***	-0.0878***
	(0.0232)	(0.0232)
Total rain in season	-	-0.0000573
		(0.00006)
N	2,774	2,774

Standard errors in parentheses.

Table 4
Farmer Fixed-Effect Estimates of the Effects of the IMD Forecast and Forecast Skill on Log Planting-Stage Investment, REDS 1999-2007

Variable	(1)	(2)	(3)	(4)
IMD forecast	-0.0232	-0.0604	-	-
	(0.0303)	(0.0397)		
IMD forecast x *q*	-	0.166***	-	-
		(0.0788)		
Forecast<98	-	-	0.309	0.543***
			(0.199)	(0.229)
Forecast<98 x *q*	-	-	-	-1.514***
				(0.548)
N	4,438	4,438	4,438	4,438

Standard errors clustered at the village level in parentheses. *q*=district-average of the correlations of IMD forecasts with village-level rainfall in the 242 ARIS/REDS villages, 1999-2006 where positive.

Concern: forecast skill may be correlated with other area characteristics that affect behavior.

Two issues:

A. Is forecast skill correlated spatially with soil and weather conditions, crops or even infrastructure?

B. If so, does the investment response to the forecast depend as well on these characteristics?

The REDS data provide in addition to rainfall soil characteristics, crop choices, and infrastructure.

We look at the cross-district association between whether a district has forecast skill, average *q* and:

The average level and cv of rainfall

The fraction of rice-growing farmers

Whether there is a bank near the village (< 5 km)

4 soil characteristics

Result: these are correlates of skill, but do not influence the forecast response net of skill when we include them in the specification.

Now we look at weather and forecast effects on profits and their interactions to further confirm that $\gamma < 1$ using two data sets.

Also we quantify the payoffs to farmers from better forecasts.

A. We use the ICRISAT panel data 2009-2014 for the villages with skill.

   Kharif-season real profits.

   Kahrif season total rainfall.

   We categorize the forecast as B if the forecast is for <98% of normal rainfall.

B. We use the ARIS panel data 1968-71, for the skill districts.

In those years, the forecast was given in simple categories:

Normal (0), above normal (1), below normal (-1), much below normal (-2).

Limitations:

We have for weather only the simple dichotomous variable: adverse weather in the village or not.

We use the skill measures based on the 1999-2007 rainfall time-series for these same villages (REDS).

Table 7
Farmer Fixed-Effect Estimates of Rainfall and the IMD Forecast Effects on *Kharif*-Season Farm Profits: ICRISAT Villages, 2009-2014

Variable	(1)	(2)
Total village rainfall (mm) in *Kharif* season	88.1***	98.0***
	(12.2)	(13.2)
Rainfall squared	-0.0425***	-0.0457***
	(0.00638)	(0.00654)
Forecast<98 x rainfall	-	10.3
		(7.35)
Forecast<98 x rainfall squared	-	-0.0137**
		(0.00710)
(a) $d\pi/dRain$ with good forecast at mean rainfall:	-	36.6***
		(5.68)
(b) $d\pi/dRain$ with bad forecast at mean rainfall:	-	28.5***
		(5.51)
(a) - (b)	-	8.04***
		(3.55)
N	2,478	2,478

Table 8
Farmer Fixed-Effect Estimates of the Effects of Weather, the IMD Forecast and Forecast Skill on Farm Profits, ARIS 1968-71

Variable	Districts with Skill		Districts with No Skill	
Bad weather in village	-1178.5	-1214.3	-290.8	-270.5
	(762.4)	(860.9)	(201.5)	(213.1)
IMD forecast	518.9	-251.5	-24.73	-60.31
	(452.2)	(492.8)	(279.0)	(314.7)
IMD forecast x *q*	-3698.8	5024.8**	-	-
	(3099.5)	(2549.9)		
Forecast x bad weather	-	224.3	-	139.3
		(865.0)		(417.0)
Forecast x *q* x bad weather	-	-5171.5***	-	-
		(2330.2)		
N	1,208	1,208	5,484	5,484

Standard errors clustered at the village level in parentheses. *q*=district-average of the correlations of IMD forecasts with village-level rainfall in the 242 ARIS/REDS villages, 1999-2006 where positive.

We can also use the ARIS panel data to test whether a good forecast increases risk taking.

The ARIS was initiated just when HYV seeds were introduced.

Not only were the payoffs from these seeds unknown to the farmers, but the seeds themselves were known to be substantially more sensitive to rainfall.

Planting HYV seeds in 1968-71 was indeed a risky choice, and thus HYV planting is a good measure of R.

We can see if a forecast of bad weather reduced HYV adoption for the same farmer over time where the forecast has skill.

Table 9
Farmer Fixed-Effect Estimates of the Effect of the IMD Forecast by Forecast Skill on Planted HYV Acreage: ARIS 1968-71

Variable/sample	Districts with Skill	Districts with No Skill	All districts	
IMD forecast	2.636***	0.663	0.663	1.486***
	(1.135)	(0.528)	(0.532)	(0.636)
IMD forecast x skill area	-	-	1.973	-
			(1.209)	
IMD forecast x *q*	-	-	-	4.321***
				(2.061)
N	1,200	5,373	6,573	6,573

Standard errors clustered at the village level in parentheses. Skill area=district-average of the correlations of IMD forecasts with village-level rainfall in the 242 ARIS/REDS villages, 1999-2006>0. *q*=district-average of the correlations of IMD forecasts with village-level rainfall in the 242 ARIS/REDS villages, 1999-2006 where positive.

We have seen that a forecast of B decreases farmer investment and risk-taking, and the more so where forecast skill if higher, consistent with the model.

Now we look at the supply side: planting stage migration by males age 19-59 in July/August

We use:

A. The ICRISAT panel of households 2009-2014

B. NSS panel of districts 2005-2007, 2009.

Does a forecast of B induce planting-stage migration?

Does an increase in the minimum wage reduce the impact of the forecast effect?

Table 10
Household Fixed-Effect Estimates of the IMD Forecast and Minimum Wage Effects on *Kharif*-Season Planting-Stage Migration by Men Aged 19-49
ICRISAT Villages, 2009-2014

Year/area	(1)	(2)
Forecast<98	0.0235***	0.184***
	(0.00514)	(0.0745)
Real minimum wage	-0.000948***	0.0000219
	(0.000431)	(0.000451)
Forecast<98 x minimum wage	-	-0.00165***
		(0.000759)
N	8,025	8,025

Standard errors in parentheses clustered at the household level. Specification also includes the age and age squared of the respondent.

Table 11
District Fixed-Effect Estimates of the IMD Forecast and Minimum Wage Effects on *Kharif*-Season Planting-Stage Migration by Rural Men Aged 19-49
NSS Rounds 62,63,64, and 66 ARIS/REDS Districts

Year/area	(1)	(2)
Forecast<98	0.0400***	-0.103
	(0.0176)	(0.123)
Forecast<98 x *q*	0.723***	8.543***
	(0.130)	(0.689)
Real minimum wage	-0.292	0.140
	(0.233)	(0.421)
Forecast<98 x minimum wage	-	0.998
		(0.628)
Forecast<98 x minimum wage x *q*	-	-45.4***
		(3.946)
N	3,907	3,907

Standard errors in parentheses clustered at the household level. Specification also includes the age and age squared, schooling and total owned land of the respondent and the mean rainfall and standard deviation of rainfall in the sampling unit. *q*=district-average of the correlations of IMD forecasts with village-level rainfall in the 242 ARIS/REDS villages, 1999-2006, where positive.

So, a forecast of B decreases investment and risk-taking by farmers, decreasing labor demand in the planting stage and thus lowering wages.

But, we also see that there is more out-migration, which makes labor more scarce.

So, what happens to planting-stage wages when there is a forecast of B?

Does an increase in the minimum wage on average lower planting-stage wages when the forecast is B due to anticipatory migration?

Table 12
Household Fixed-Effect Estimates of the IMD Forecast and Minimum Wage Effects on *Kharif*-Season Planting-Stage Log Wages for Men Aged 19-49
ICRISAT Villages, 2009-2014

Year/area	(1)	(2)
Forecast<98	0.0569***	1.514***
	(0.0199)	(0.244)
Real minimum wage	0.00239**	0.0112***
	(0.00143)	(0.00199)
Forecast<98 x minimum wage	-	-0.0149***
		(0.00244)
N	5,139	5,139

Standard errors in parentheses clustered at the household level. Specification also includes the age and age squared of the respondent.

Table 13
District Fixed-Effect Estimates of the IMD Forecast and Minimum Wage Effects on *Kharif*-Season Planting-Stage Log Wages for Rural Wage Workers Aged 19-49
NSS Rounds 61,66, and 68 ARIS/REDS Districts

Year/area	(1)	(2)
Forecast<98	-0.283	-1.016
	(0.225)	(1.131)
Forecast<98 x *q*	0.593	7.675***
	(0.646)	(3.382)
Real minimum wage	1.477	1.758
	(1.632)	(1.760)
Forecast<98 x minimum wage	-	4.126
		(4.777)
Forecast<98 x minimum wage x *q*	-	-35.24***
		(15.37)
N	3,023	3,023

Standard errors in parentheses clustered at the household level. Specification also includes the age and age squared, schooling, and gender of the respondent and the mean rainfall and standard deviation of rainfall in the sampling unit. q=district-average of the correlations of IMD forecasts with village-level rainfall in the 242 ARIS/REDS villages, 1999-2006, where positive.

Now we can look at harvest migration and wages.

Two key predictions from the model involve interactions of the forecast with rainfall and the minimum wage respectively:

A. The harvest wage gain from a good(bad) forecast will be greater(less) if it rains more.

B. An increase in the minimum wage can <u>decrease</u> harvest wages on average when there is a forecast of bad weather (if minimum wages are binding at the planting stage).

We should also see that

A. More rainfall decreases harvest migration and increases the harvest wage.

B. An increase in the minimum wage decreases harvest migration and raises the harvest wage.

C. An increase in the minimum wage decreases harvest migration and raises the harvest wage less in good weather.

Table 14
Household Fixed-Effect Estimates of the IMD Forecast and Minimum Wage Effects on *Kharif*-Season Harvest-Stage Migration for Men Aged 19-49
ICRISAT Villages, 2009-2014

Year/area	(1)	(2)
Village rainfall (mm)	-0.00000201	-0.0000669**
	(0.00006)	(0.0000349)
Forecast<98	0.0163***	0.203***
	(0.00422)	(0.0809)
Real minimum wage	-0.000816***	-0.00021
	(0.000394)	(0.000539)
Forecast<98 x rain	-	-0.0000685**
		(0.0000365)
Minimum wage x rain	-	0.00000155***
		(0.000000641)
Forecast<98 x minimum wage	-	-0.00166***
		(0.000761)
N	9,621	9,621

Standard errors in parentheses clustered at the household level. Specification also includes the age and age squared of the respondent.

Table 15
District Fixed-Effect Estimates of the IMD Forecast and Minimum Wage Effects on *Kharif*-Season Harvest-Stage Migration of Rural Men Aged 19-49
NSS Rounds 62,63,64, and 66 ARIS/REDS Districts

Year/area	(1)	(2)
Village rainfall (mm)	-0.000186***	-0.000620***
	(0.000061)	(0.000179)
Forecast<98 x q	-0.481***	1.072
	(0.0833)	(1.970)
Real minimum wage	-3.141***	-3.072***
	(0.177)	(0.218)
Forecast<98 x minimum wage x q	-	-14.94
		(11.36)
Forecast<98 x q x rain	-	-0.00947***
		(0.00132)
Minimum wage x rain	-	0.00206***
		(0.000319)
N	3,833	3,833

Standard errors in parentheses clustered at the district level.

Table 16
Household Fixed-Effect Estimates of the IMD Forecast and Minimum Wage Effects on *Kharif*-Season Harvest-Stage Log Wages for Men Aged 19-49
ICRISAT Villages, 2009-2014

Year/area	(1)	(2)
Village rainfall (mm)	0.000660***	0.00346***
	(0.0000861)	(0.000759)
Forecast<98	0.0567***	1.99***
	(0.0211)	(0.301)
Real minimum wage	0.00493***	0.0238***
	(0.00135)	(0.00218)
Forecast<98 x rain	-	-0.000441**
		(0.000123)
Minimum wage x rain	-	-0.0000343***
		(0.00000784)
Forecast<98 x minimum wage	-	-0.0186***
		(0.00283)
N	6,007	6,007

Standard errors in parentheses clustered at the household level. Specification also includes the age and age squared of the respondent.

Table 17
District Fixed-Effect Estimates of the IMD Forecast and Minimum Wage Effects on *Kharif*-Season Harvest-Stage Log Wage of Workers Aged 19-49
NSS Rounds 62,63,64, and 66 ARIS/REDS Districts

Year/area	(1)	(2)
Village rainfall (mm)	0.000330***	0.000695
	(0.0000776)	(0.000527)
Forecast<98 x q	-0.775***	2.903
	(0.155)	(2.116)
Real minimum wage	3.12***	3.253***
	(0.475)	(0.430)
Forecast<98 x minimum wage x q	-	-16.49
		(11.22)
Forecast<98 x q x rain	-	-0.00114***
		(0.000521)
Minimum wage x rain	-	-0.00204
		(0.00290)
N	16,774	16,774

Standard errors in parentheses clustered at the district level.

Conclusion

Migration has been overlooked in the empirical literature for many years, but there is now new research.

Clear that temporary migration is large scale and responsive to economic conditions.

> Analyses of policies and even of short-term RCT interventions need to take into account migration responses.
>
> Equilibrium effects can be large, so more attention to those.

Risk play a large role in economic decisions, including migration.

Any policy or intervention that affects risk will thus affect migration.

Characterizing risk - its endogenous and exogenous components and its spatial aspects - needs improvement.

Networks play a large role in migration, both directly (facilitating moves) and indirectly, by altering the gains and costs of migration via risk-sharing.

Need more attention to the scope and scale of networks to better characterize their role.

Inclusive of network's role in coordinating production - none?

See much more new work on temporary migration compared with permanent migration: data!

Easier to catch in short-term surveys - migration corresponds to the time frame of most one-year projects.

Easy to catch in household surveys - temporary migrants are by definition members of households.

Permanent migrants are no longer household members.

Need to think more about the data required to study long-term, permanent moves by household members and whole households.