NBER WORKING PAPER SERIES

ASSESSING THE BENEFITS OF LONG-RUN WEATHER FORECASTING FOR THE RURAL POOR: FARMER INVESTMENTS AND WORKER MIGRATION IN A DYNAMIC EQUILIBRIUM MODEL

Mark R. Rosenzweig
Christopher R. Udry

Working Paper 25894
http://www.nber.org/papers/w25894

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2019

Assessing the Benefits of Long-Run Weather Forecasting for the Rural Poor: Farmer Investments and Worker Migration in a Dynamic Equilibrium Model
Mark R. Rosenzweig and Christopher R. Udry
NBER Working Paper No. 25894
May 2019
JEL No. O1,Q12

ABSTRACT

The livelihoods of the majority of the world's poor depend on agriculture. They face substantial risk from fluctuations in weather conditions. Better risk, credit and savings markets can improve productivity and welfare in rural areas but entail high administrative costs. We consider a classic public good with benefits that theoretically exceed those of perfect insurance contracts – improving the skill of long-run weather forecasts. We use an equilibrium model of agricultural production and labor migration, and a variety of Indian panel datasets to assess quantitatively the effects of improvements in seasonal forecasts of monsoon weather. We find that in areas where the forecast is accurate (has “skill”) that investment, migration and rural wages respond to forecasts. We calculate that if such skill were pervasive across India, the total value of an accurate forecast for farmers and wage workers is in the tens of billions of rupees.

Mark R. Rosenzweig
Department of Economics
Yale University
Box 208269
New Haven, CT 06520
and NBER
mark.rosenzweig@yale.edu

Christopher R. Udry
Northwestern University
Department of Economics
Weinberg College of Arts and Sciences
2211 Campus Drive #3247
Evanston, IL 60208
and NBER
christopher.udry@northwestern.edu

The majority of the world's poor reside in rural areas. A salient feature of rural populations in low-income countries is that population density is low even in densely-populated countries. A major consequence is that service delivery to the poor is expensive, especially for services that require monitoring. For example, given that most rural residents in low-income countries are engaged in small-scale agriculture, one of the major issues they face is variability in incomes due in large part to fluctuations in rainfall (Rosenzweig and Udry, forthcoming; Cole and Xiong, 2017). Risk mitigation is thus a key desideratum for assisting the poor. Yet, while research has shown that index-based insurance contracts (Karlan *et al*., 2016) effectively mitigate the consequences of riskiness, improve farm profitability, and can reduce income risk for the landless (Mobarak and Rosenzweig, 2014), loading costs associated with marketing, payment disbursement and weather station construction and maintenance, given the number of small farms, render such contracts, if priced to incorporate such costs, out of reach for most rural inhabitants (Carter *et al*., 2017). Similarly, the disbursement of loans to households, small-scale enterprises and farms entail high administration costs (Banerjee *et al*., 2015). Even seemingly less costly measures such as providing low-cost, safe and effective access to saving technologies has proven difficult in many developing countries (Dupas and Robinson, 2013).

Technology gives hope, however, that the costs of service or information delivery can be reduced or bypassed relatively cheaply. A key example of exploiting new technology to overcome administrative costs is cell phone technology. Once a network is established, the marginal cost of information delivery is close to zero – the network is like a public good. Jensen (2007), for example, has demonstrated that the delivery of pricing information via cell phones substantially improved market efficiency in the fisheries sector and Suri and Jack (2016) show that the availability of cell-phone based monetary transaction apps enabled households to better cope *ex post* with income variability and facilitated savings.

An alternative means of mitigating the consequences of weather fluctuations for poor populations in the absence of markets for unsubsidized insurance contracts is to harness technology to directly reduce weather risk. Long-term weather forecasting is an example of a technology-intensive public good that has minimal delivery costs and can reduce the principle source of income risk for the poor.[1] Like actuarially fair insurance, a perfectly accurate forecast of this year's weather pattern, provided before a farmer makes his or her production decisions for the season, eliminates weather risk. However, a perfect forecast also permits the farmer to make optimal production choices conditional on the realized weather and thus achieve higher profits on average compared with even a perfectly-insured farmer. Similarly, the rural landless can make better choices about migration if informed about future rainfall. Most importantly, a forecast is information that can be delivered via cell phone networks or by broadcast. The returns to enhancing individual-farmer risk reduction by improving the accuracy of inter-annual weather forecasts are thus potentially high, given the small costs of delivery compared with those associated with traditional contractual services (credit, insurance), however well-designed to facilitate coping with the consequences of rainfall realizations.

Long-term – seasonal or inter-annual - rainfall forecast skill has benefitted from recent advances in technology, from improved computational power, from better models that exploit the El Nino

[1] Additionally, agricultural scientists have exploited advances in molecular genetics to improve the *ex ante* options available to farmers faced with uninsured weather risk, most prominently by developing drought-tolerant varieties of important crops. These advances benefit all farmers and do not entail extra delivery expenses.

southern oscillations (ENSO), and from increases in observational capacity for the key elements feeding weather models – snow cover, polar ice caps (cryosphere), and sea surface temperature (SST) anomalies - via increases in the number and sophistication of satellites and buoys (e.g., Stockdale *et al*., 2010; Balmaseda *et al*., 2009). And it is expected that forecast skill will continue to improve in the foreseeable future (National Research Council, Division on Earth and Life Studies, Board on Atmospheric Sciences and Climate, Committee on Assessment of Intra-seasonal to Inter-annual Climate Prediction and Predictability, 2010). Governments are aware of and responding to this opportunity. In India the national Monsoon Mission was launched in 2012 with a budget of $48 million for five years to support research on improving forecast skill, with a special focus on seasonal weather forecasting.[2] There is nothing new about this; in India the India Meteorological Department (IMD) has been issuing annual forecasts of the monsoon across the subcontinent since 1895, and it is widely reported in the Indian media that farmers' livelihoods depend upon the accuracy of the forecast.[3]

While, as we discuss below, the accuracy of the IMD monsoon forecast is on average marginal, the forecasts are evidently taken very seriously among all sectors of the Indian economy. The NIFTY 50 index is the National Stock Exchange of India's index for the Indian equity market. None of the sectors represented in the index is directly affected by rainfall, as neither farms nor agricultural processing enterprises are included, and only eight percent of the stocks are in the consumer sector. Nevertheless, the index responds significantly to the announcements by the IMD of monsoon rainfall, both the preliminary announcement in April and the final prediction at the end of June. Figure 1 displays the average percent change in the index the day after the announcement by the IMD of a pessimistic forecast and the average percent rise when the forecast was optimistic for the ten forecasts issued over the period 2013-2017 relative to two major consequential events that also occurred during that time – the UK BREXIT vote and the demonetization of the Indian rupee. While these latter events had major impacts on the equity market, the response to the IMD forecasts was also significant – the index rising 0.8 percent when the forecast was positive and falling 0.6 percent when negative, the 1.4 percent difference (64 percent of the BREXIT decline) being statistically significant at the 0.02 level (t=2.87).

Although Figure 1 suggests the importance of both weather outcomes and the existence of direct forecast effects on the overall economy in India, there is as of yet no rigorous assessments of the impact of long-term weather forecasts and improvements in weather forecast skill on the rural poor. There is a substantial literature dedicated to *ex-ante* simulations of the value of improved weather forecasts that employs simulations of dynamic crop models to estimate the potential effect of forecast information of farm profits and crop prices (Meza *et al*., 2008). There is also work based on survey and ethnographic evidence exploring farmers' use (or not) of information from weather forecasts in their farming decisions (Roncoli, 2006; Mase and Prokopy, 2013). The crop model simulations yield varied results, but typically predict a large economic value for long-term forecast information (e.g., $5-15 per

---

[2] The annual budget for the US National Oceanic and Atmospheric Administration, which is responsible for forecasting research (among other responsibilities) in the US, was approximately $5 billion in 2010.
[3] For example, "Laxman Vishwanath Wadale, a 40-year-old farmer from Maharashtra's Jalna district, spent nearly 25,000 on fertilisers and seeds for his 60-acre plot after the Indian Meteorological Department (IMD) said in June that it stands by its earlier prediction of normal monsoon. Today, like lakhs of farmers, Wadale helplessly stares at parched fields and is furious with the weather office that got it wrong — once again. So far, rainfall has been 22% below normal if you include the torrential rains in the northeast while Punjab and Haryana are being baked in one of the driest summers ever with rainfall 42% below normal" (Ghosal and Kokata 2012).

hectare per year in US and Argentinian agriculture, Jones *et al*., 2000). The survey and ethnographic evidence shows great interest on the part of farmers in forecast information. Nesheim *et al*. (2017) show that fifty percent of farmers in three case study villages in Maharashtra rely on broadcast weather information when making sowing decisions. We have found no research, however, that evaluates the impact of long-term weather forecasts on the incomes or welfare of the rural poor using data measuring actual behavior, agricultural outcomes and earnings.[4]

In this paper, we use information on the IMD forecasts and rainfall to quantify the effects of the forecasts and forecast skill on the incomes of the rural population, both cultivators and agricultural wage workers, using a variety of panel data sets. To do that we need to employ an equilibrium model, because the forecast simultaneously affects all agents in the economy. We also need to recognize the sequential nature of agricultural production and that temporary migration is a major factor in determining the supply of workers to agricultural production in a given locale. We thus set out a parsimonious dynamic equilibrium model of the local rural economy. The model incorporates a number of important features of an agricultural setting. First, the model recognizes the necessity of making (*ex ante*) agricultural investments prior to the resolution of uncertainty (rainfall realizations). Second, the model incorporates two types of *ex ante* investment decisions by farmers that can be influenced by the forecasts: the level of inputs (labor) to employ; and the choice of production technology, characterized by the sensitivity of output to rainfall (riskiness). Third, the model includes two migration (labor supply) decisions by landless workers, who can choose to migrate *ex ante* out of their home village in response to the forecast but prior to the realization of rainfall and/or *ex post* in response to the realization of weather. An important property of the model is that initial-period investment and migration decisions affect outcomes (farm profits, wages) in later periods because of the dynamic elements of the model and thus incomes (wages) vary within a season due to the interactions of aggregate demand and supply.

There are three novel features of the model. First, the model incorporates both migration (labor supply) and production (labor demand) decisions. Prior studies of rural temporary migration that examine the impacts of interventions that raise the returns to migration have not examined how such interventions affect local farmers' (employer's) decisions. Typically, even in structural models of migration (Morten, 2019; Meghir *et al*., 2017), the parameters of the income process, while allowed to change due to the specific counter-factual intervention considered, are not the products of optimizing behavior and thus are not invariant to alternative policies. A second novel feature of the model is that it examines both *ex ante* and *ex post* migration and their dynamic interactions. Studies of temporary migration have looked at only one type of migration at a time – either off-season migration, when demand is predictably low, (e.g., Bryan *et al*., 2014) or *ex post* migration within a growing season that responds to realized weather shocks (Morten, 2019). In our model, <u>within</u> the growing season there is both *ex ante* (anticipatory) and *ex post* migration.

As far as we know, there are no studies of temporary migration in the early stages of the growing season in India. Yet, such anticipatory migration appears to be important and to vary across years. Figure 2 reports the fraction of male rural workers age 19-49 employed in urban areas by month from the 18 villages in the International Crop Research Institute of the Semi-Arid Tropics (ICRISAT)

[4] "Resolving the uncertainty about the value of seasonal climate prediction to agriculture requires rigorous ex-post impact studies, after forecasts have been widely communicated and supported adequately for a long enough period to allow learning, adaptation and wide-spread adoption" (Meza et al., 2008, p.1283).

village survey over the period 2010-2014. As can be seen, migration rates sharply increase at the start of the *kharif* growing season, which begins in July and ends in late Fall, and immediately after the final IMD monsoon forecast, with six percent of men migrating out. As seen in Figure 3, monthly data on rural workers away from home, by duration, from the National Social Surveys (NSS) for the same demographic group show a similar pattern across all of India, with out-migration peaking in July, at 10 percent for those away at least one day. Finally, the ICRISAT data, as displayed in Figure 4, also show that the July rates of migration varied substantially across years, peaking at over 11 percent in 2010 and reaching a low of three percent in the middle of the survey period. This intertemporal variation in out-migration could be due to variation in the forecast, which we will test more rigorously.

We believe the dynamic equilibrium model is useful for examining the impact in rural areas of any large-scale program or policy. Besides considering the consequences of forecasts, we also use the model to assess how investments, profits, the two types of migration, and equilibrium wages are affected by variation in the statutory minimum wages associated with the National Rural Employment Guarantee Act (NREGA) of 2005 and, importantly, how changes in minimum wages interact with the forecasts in affecting outcomes. We examine the effects of the minimum wages because over the period in which we look at forecast effects there was substantial intertemporal variation in nominal statutory minimum wages, with such (nominal) wages changing as much as seven times over the period 2005-2012 in some states, and such variation, as we show, can affect the impacts of forecasts.[5] While recent work evaluating NREGA on equilibrium wages has shown that NREGA statutory wage effects depend on rainfall realizations (Santangelo, 2019), no evaluations of NREGA on equilibrium wages (e.g., Berg *et al*., 2013; Imbert and Papp, 2015) examine both the effects of the IMD forecasts and of rainfall on program wage effects during the period and in the areas studied. Our framework and empirical findings call into question the external validity of these estimates, as we show that the equilibrium wage effects of NREGA statutory minimum wages differ significantly across stages of agricultural production, by the IMD forecast as well as by rainfall.

In section 2 we set out the model. The model delivers predictions for how forecasts affect planting-stage farmer investments and technology choice and the planting-stage migration decisions of workers, and how forecasts and rainfall and their interactions affect farm profits, migration and equilibrium wages in the harvest stage. The model also indicates that increases in the minimum wage blunt the effects of forecasts on both farm decisions and on migration. As a consequence, while increases in minimum wages can never lower the welfare of workers, we show that they can reduce equilibrium wages in the planting stage or in the harvest period (but not both in the same season). In section 3, we begin the empirical work by assessing the skill of the IMD forecasts over the period 1999-2011 using ground-based information on growing-season monthly rainfall at the village level from the ICRISAT survey and from a national survey. We find that overall the forecasts have little skill, but we identify contiguous areas of India in which forecast skill is significant. We explore how skill is related to a variety of agro-climatic attributes, showing that such attributes predict which areas have skill, but not skill variation within the areas with skill.

[5] Variation in the forecasts and in rainfall amounts and their timing are orthogonal to agents' behavior and characteristics, net of fixed effects, so that empirically they allow us to assess the model predictions and evaluate their effects, with confidence in their internal validity. Variation in statutory minimum wages is less pristine, and empirical identification of their effects should be interpreted with more caution.

In section 4, we use ICRISAT panel data and panel data from the national Rural Economic Development Survey (REDS) and the Additional Rural Income Survey (ARIS) to estimate the effects of the forecasts and forecast skill on planting-stage investments and on the planting of risky high-yielding variety crops at the onset of the Indian green revolution. We find that, consistent with the model, a forecast of poor weather lowers planting-stage investments and lowers risk-taking, and the more so the higher the skill level of forecasts in the area. For example, we find using the ICRISAT panel data that a pessimistic forecast lowers planting-stage investments by 15.8 percent overall, but by over 18 percent in the villages located where forecasts have skill, compared with only 4.4 percent in the villages where forecasts have little skill.

We next quantify the gains to farmers in terms of profitability from receiving accurate forecasts. Consider a one standard deviation change in seasonal total rainfall (from one-half standard deviation above average in a "good" season to one-half standard deviation below average in a "bad" season). We find that over the period 2009-2014 in the ICRISAT villages in which the forecasts have skill that profits are increased by 11.5 percent when forecasts are correct. Of course, if the forecasts are incorrect, this is the loss. The net gain from the availability of forecasts stems from the forecasts being correct more than half the time – thus, the greater the forecast skill the greater the gain, even ignoring that increases in forecast skill also amplify farmers' responses, which enhances the net gain.

In section 5 we use both the ICRISAT and NSS data and find, again consistent with the model, that a pessimistic forecast increases outmigration in the planting period. In particular, we find using the ICRISAT panel of agricultural workers that a pessimistic forecast increases out-migration by 2.4 percentage points, a 37 percent increase at the sample mean out-migration rate. As implied by the model, the forecast effect on out-migration is also reduced significantly where real statutory minimum wages are higher – when the forecast is pessimistic, a one-standard deviation increase in the minimum wage lowers the positive effect of the forecast on out-migration by 64 percent. While the net effect of a pessimistic forecast on equilibrium planting-stage wages, given its negative effect on worker demand and risk-taking, is theoretically ambiguous, we find in section 6 that on net a forecast of below normal rainfall increases wages in the planting stage, suggesting the out-migration effect dominates. Consistent with the model, however, we also find from both data sets that an increase in the minimum wage when the forecast is pessimistic lowers the equilibrium wage - a one-standard deviation in the real minimum wage decreases the planting-stage equilibrium wage by almost 3.7 percent when the forecast suggests a low-rainfall kharif season.

In section 7, we estimate how the monsoon forecast, rainfall and minimum wages affect harvest-stage migration and harvest-stage equilibrium wages using the ICRISAT panel and its village-level rainfall information. In alignment with the model, we find that out-migration at the harvest stage is lower when rainfall and the minimum wage are higher, but out-migration is higher when the planting-stage forecast was pessimistic. We also find that higher rainfall and a forecast of a poor monsoon raise harvest wages as do higher minimum wages on average. The interactions between rainfall, the forecasts and minimum wages are also significant, however. In accordance with the model, real harvest-stage wages rise less with rainfall in areas where minimum wages are higher and if there was a pessimistic forecast. And the positive effect of a rise in the minimum wage on equilibrium harvest wages is less when the forecast predicted a bad monsoon, with again a higher minimum wage actually lowering the equilibrium harvest wage in a state of the world in which the forecast was pessimistic and incorrect. Given our estimates, and model, we find that the gains to workers from accurate forecasts are modest, since they accrue from migration out of bad-weather areas and migration rates are relatively low and respond weakly to the forecast. Specifically, we find that an accurate forecast only increases a migrant's income by 25 rupees. This again is a lower bound estimate, since our results show that the responsiveness to forecast rises sharply with forecast skill. Still, even given the relatively low level of temporary migration, the total gain at this lower bound, given the number of rural wage workers, is Rs. 61 million, on top of our lower-bound estimate of the total gains to cultivators of Rs. 29.1 billion. Section 8 contains our conclusion.

2. The Model

Seasonality and risk shape the economic lives of the rural population of India, both landed and landless. We provide a simple model to describe decision-making by landowning farmers and landless workers and their interactions in rural labor markets over the course of the agricultural cycle as information about the likelihood of future shocks is revealed and shocks themselves are realized. The decisions at the heart of the model are the magnitudes and riskiness of the planting season investments made by farmers, and the seasonal migration choices of the landless.

<u>a. Environment</u> We model a single farming season, during which there are two periods, which we call *stages:* planting (1) and harvesting (2). In the empirical work we will allow for the reality that the resources available to a farmer at the start of stage 1 reflect prior decisions, forecasts and realization of shocks, but the model abstracts from these considerations in order to focus on the intra-season allocation across stages and states of nature.

Before stage 1, a forecast $F \in \{B, G\}$ of the harvest-stage state is announced. The harvest stage realized state is $s \in \{b, g\}$. Let $q = prob(s = b|F = B) = prob(s = g|F = G)$ be the forecast skill. This assumption implies that forecast error probabilities are symmetric, but this simplification has little consequence in the analysis of the model and in fact describes the actual performance of the IMD forecast. Consumption occurs in both the planting and harvest stage, so there are six stages/realized states to consider. Consumption in stage one, which may depend upon the forecast F is denoted by c_{1G} and c_{1B}. Consumption in stage two, which may depend upon both the forecast F and the realized state in the harvest stage, s, is c_{sF} (so, for example, consumption in the good state of the harvest stage in a season that had been forecast to be bad is c_{gB}). We abstract from labor/leisure choices and assume that each individual inelastically supplies one unit of labor in each stage. All agents have constant relative risk aversion preferences:

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

<u>b. Cultivators.</u> There is a mass 1 of landed cultivators each with a fixed land endowment. Each cultivator works full time on his own plot. Farm output is generated by the cultivator combining his own land and labor with some amount of hired labor (x_{1F}) used during the planting stage of the season and hired labor (x_{gF}, x_{bF}) used in the good or bad state realized during the harvest stage of the season. The cultivators also choose in the first stage the riskiness of the portfolio of crops that they plant ($R_F \in [0,1]$). After forecast F, farm output in state s of the harvest stage is Q_{bF}.

$$Q_{bF} = \min\left(x_{1F}^{\beta}(1 - R_F), \frac{x_{bF}}{\rho}\right) \tag{2}$$

$$Q_{gF} = \min\left(\theta x_{1F}^{\beta}(1 + R_F), \frac{x_{gF}}{\rho}\right)$$

This is a conventional Cobb Douglas production function with diminishing returns to labor in the planting stage, except that the choice of R affects the gap between output in the good and bad states. $\theta > 1$ represents the additional output that is received in the good state when a farmer takes on additional risk.

Harvest stage production is Leontief in labor use: $x_{sF} = \rho Q_{sF}$. We assume that farmers have no access to insurance, nor to financial savings or borrowing. Therefore, farmers shift resources across stages and states of nature through their decisions regarding the extent and riskiness of their cultivation activities. A farmer wishing to consume more in the planting stage reduces the amount of planting stage labor; a farmer wishing to consume more in the bad state of the harvest stage reduces planting season labor expenditure and reduces the riskiness of the mix of his farming activities.[6] In the absence of a safe asset or credit market, the choice of planting stage labor is the primary tool for moving resources across stages, while the choice of the riskiness of the technology is the first order tool for calibrating risk across harvest stage states of nature. But the absence of complete asset markets implies that these two decisions cannot fully be separated.

The budget constraints of a farmer after forecast F in stage 1 and in state s of stage 2 are:

$$\begin{aligned} c_{1F} &= Y_c - w_{1F}x_{1F} \\ c_{sF} &= Q_{sF}(1 - \rho w_{sF}) \end{aligned} \qquad (3)$$

At the time the farmer chooses x_{1F} and R_F, the forecast is known, as is the planting stage wage (w_{1F}). The farmer also knows the forecast skill (q) and thus the probability that the good or bad state will be realized in the harvest stage. In addition, the farmer knows the harvest stage wage that will prevail if state s is realized in the harvest stage (w_{gF}, w_{bF}), given the forecast.

Given a forecast (F) and the vector of state- and forecast-specific wages $w_F = (w_{1F}, w_{gF}, w_{bF})$, a farmer chooses planting stage labor (x_{1F}) and the level of risk (R_F) to maximize (1) subject to (2) and (3).

c. Landless workers. Landless workers have the same preferences as farmers, but they are endowed only with labor. Their only choice in each stage is to work for a wage in the village, or to migrate to the city and work there. Simultaneous with the revelation of the forecast before the planting stage, each landless individual receives an urban wage offer for the planting stage (w_{1u}). This offer is drawn from a common distribution $\mathcal{F}_1(w)$.[7] After this wage offer is revealed, the worker decides whether to migrate to the urban area or not. We denote the worker's decision to migrate or not in the

[6] In this simple model with two states of nature, and only two periods, access to a safe asset would permit each farmer to separate his decisions regarding cultivation and risk-bearing, choosing R_F to maximize returns and the investment in the safe asset versus cultivation to adjust the extent of risk borne. More generally, this separation property will fail to hold and $R_F$depends upon the extent of risk aversion whenever the financial assets available to the farmer fail to span the state space.

[7] We assume that the distribution of urban wage offers $\mathcal{F}_1(w)$ (and later, $\mathcal{F}_2(w)$) are independent of the forecast. This simplification permits us to focus on changes in rural wages without a full model of equilibrium in urban labor markets, thus abstracting from the possible indirect effects of rural weather forecasts and realizations on the urban labor market.

planting stage after a forecast of F as $m_F \in \{0,1\}$. Similarly, before the harvest stage, simultaneously with the revelation of the realized state for the harvest stage in the village, each landless worker receives another urban wage offer for the harvest stage (w_{2u}). After this wage offer is received, the worker again decides whether to work in the urban area (migrate) or to work in the village.

Therefore, the budget constraint of a landless worker is

$$c_{1F} = I(m_F = 1)w_{1u} + \big(1 - I(m_F = 1)\big)w_{1F} + Y_l$$
$$c_{sF} = \max(w_{2u}, w_{sF}) \tag{4}$$

The urban wage offers for the planting stage are drawn from a uniform distribution

$$w_{1u} \sim \mathcal{F}_1(w) = wf_1, \tag{5}$$

where f_1 is a positive constant. The urban wage offers drawn for the harvest stage are drawn from (uniform) distributions that depend on the planting stage residence of the worker:

$$w_{2u} \sim I(m_F = 1)\mathcal{F}_2(w) + \big(1 - I(m_F = 1)\big)\mathcal{F}_1(w). \tag{6}$$

We assume that a worker is more likely to attract a better urban wage offer if the worker is resident in the urban area. Therefore, we specify that $\mathcal{F}_2 = wf_2$, $f_2 < f_1$ so $\mathcal{F}_2$ first order stochastically dominates $\mathcal{F}_1$. Workers maximize (1) subject to (4) – (6).

Planting-stage migration is anticipatory migration. The worker's decision to migrate in the planting stage has a dynamic component, like the farmers' planting-stage decisions, because the distribution from which the subsequent harvest-stage wage offer is drawn differs depending upon the planting-stage residence of the worker. If the worker had chosen to migrate to the city in the planting stage, he draws an urban harvest-stage wage offer from the distribution $\mathcal{F}_2(w)$, while if the worker had chosen to remain in the village in the first stage, his urban harvest-stage wage offer is again drawn from $\mathcal{F}_1(w)$. Migration to the city during planting thus has an investment component because it increases the expected value of the harvest-stage urban wage offer. As was the case for the farmer, we assume that the landless worker has no access to financial markets.[8] After forecast F, labor supply in the planting stage $\mathrm{S}_{1\mathrm{F}}$ depends upon the rural planting stage wage, and the rural wages in both the good and bad states of the harvest stage.

Harvest-stage migration is *ex post* migration. The worker's decision to migrate in the harvest stage is taken after the state for the harvest stage is realized, and after the worker has received his or her draw from the relevant distribution of urban wages. The harvest stage decision, therefore, is simple: the worker chooses to live in the village if and only if the rural wage for the state realized in the harvest stage is at least as great as that worker's urban wage draw. Given planting stage migration decisions, labor supply in the harvest stage in state s after forecast F is

[8] A fixed cost of migration would generate similar migration decisions. In both cases, the complementarity across stages in migration decisions implies that the planting stage migration decision depends on expectations of wages in the harvest stage.

$$1 - M_{sF} = S_{sF} = S_{1F} w_{sF} f_1 + (1 - S_{1F}) w_{sF} f_2, \tag{7}$$

where the first term is the supply from village landless workers who did not migrate during the planting stage and the second term is the supply from those village workers who did migrate to the city in the planting stage. Since $f_1 > f_2$, the greater the migration out from the village during the planting stage, the lower the village labor supply during any state of the harvest stage at any wage.

d. Equilibrium. An equilibrium is defined conditional on the forecast F by a vector of wages $(w_{1F}, w_{gF}, w_{bF}) \equiv w_F$ such that

$$\begin{gathered} S_{1F}(w_F) = x_{1F}(w_F) \\ S_1 \mathcal{F}_1(w_{bF}) + (1 - S_1) \mathcal{F}_2(w_{bF}) = \rho x_b(x_{1F}(w_F)) \\ S_1 \mathcal{F}_1(w_{gF}) + (1 - S_1) \mathcal{F}_2(w_{gF}) = \rho x_g(x_{1F}(w_F)) \end{gathered} \tag{8}$$

The first equation is the equilibrium condition for the planting-season labor market and the second two equations describe equilibrium in the harvest-season good and bad states of nature. In Appendix 1, we show how to construct the equilibrium w_F and describe the characteristics of the functions $S_{1F}(w_F)$ and $x_{1F}(w_F)$.

Testable Implications of the Equilibrium Analysis

The model yields a set of testable implications, and another set that is testable depending on the degree of risk aversion. It also has testable implications regarding the effects of statutory wage floors on wages and migration, which we introduce subsequently. To understand these implications and why some of them depend upon the degree of risk aversion, it is useful to consider the three key decisions made in the planting season, after the forecast is revealed and landless individuals receive wage offers in the urban market. The decisions are the choices of cultivators regarding labor demand and the riskiness of their technology choice, and the decisions of the landless regarding migration.

Planting-stage labor demand x_{1F} is determined by the trade-off of current consumption with the expected marginal utility of the consumption to be generated by expanding planting-season expenditure on labor. The decision regarding the riskiness of a farmer's portfolio (R_F) is separable from the planting stage labor demand decision. Specifically, as we show in appendix 1, it is defined by

$$\min\left\{1, \left(\frac{prob(s = g|F)}{prob(s = b|F)}\right)^{\frac{1}{\gamma}} \left(\frac{\theta(1 - \rho w_{gF})}{(1 - \rho w_{bF})}\right)^{\frac{1}{\gamma}-1}\right\} = \frac{1 + R_F}{1 - R_F}. \tag{9}$$

The worker's planting season migration decision has a reservation property such that he migrates if and only if his urban wage offer is greater than or equal to the trigger value $w^*_{mF}(w_F)$, which depends upon the forecast and the rural wage vector. After forecast F, given a vector of wages $w_F = (w_{1F}, w_{gF}, w_{bF})$, aggregate planting stage labor supply to the village is

$$1 - M_{1F} = S_{1F} = w^*_{mF}(w_F) f_1. \tag{10}$$

We show in appendix 1 that (1) – (10) have the following four testable implications that do not depend on the risk preferences of the agents. First, regardless of the forecast, the concavity of the production function implies that an increase in the planting stage wage reduces the demand for labor $\left(\frac{dx_{1F}}{dw_{1F}} < 0\right)$. Second, regardless of the forecast, planting stage migration is decreasing in each element of the rural wage vector $\left(\frac{dM_F}{dw_{1F}}, \frac{dM_F}{dw_{sF}} < 0\right)$. Third, regardless of the forecast, harvest stage wages are higher if the good weather state is realized than if the bad weather state is realized $\left(w_{gF} > w_{bF}\right)$. Fourth, regardless of the forecast, harvest stage migration is less if the good weather state is realized then if the bad weather state is realized $(M_{gF} < M_{bF})$.

e. Regimes of Risk Aversion and Testable Implications. The above four implications would be true in a model with complete markets. However, in our model the neoclassical separation between production and consumption is absent. Some production and migration decisions, therefore, are sensitive to the degree of risk aversion (γ) and a subset of comparative static results depend upon the value of γ. It is possible, therefore, to distinguish a regime in which the agents are very risk averse $(\gamma > 1)$ from one in which the agents are less risk-averse $(0 < \gamma < 1)$. Further testable implications follow once the degree of risk aversion can be categorized as belonging to one or the other regime.

We prove in Appendix 1 that if two conditions are met, then we can conclude that $\gamma < 1$. These conditions are first, that farm profits are higher in the good weather state of the harvest stage than in the bad weather state (after a forecast of good rainfall) and, second, that the riskiness of a farmer's portfolio is greater after a forecast of good weather than after a forecast of bad weather $(R_G > R_B)$. That is

Proposition 1: If $\theta\left(1 - w_{gG}\right) > (1 - w_{bG})$ *and* $R_G > R_B$*, then* $\gamma < 1$.

If farmer profits are higher in the good state than in the bad, then a farmer with sufficiently high risk aversion $(\gamma > 1)$ pushes the riskiness of his portfolio to its minimum, sacrificing expected income in exchange for less variability. If a forecast of good weather increases the riskiness of the farmer's portfolio of activities above that chosen in the case of a bad forecast, then the consumption smoothing motive is not too strong, and $\gamma < 1$.

We verify (in Tables 4 and 7) that these two conditions are empirically satisfied and restrict further attention to the case of $\gamma < 1$. We prove in the appendix the following six testable implications of the model when $\gamma < 1$.

First, planting stage labor demand is higher after a forecast of good rain than after a forecast of bad rain:

$$x_{1G} > x_{1B} \tag{11}$$

Second, the higher investment and greater riskiness of the farmer's portfolios after a forecast of good rain than after a forecast of bad rain together imply that planting season migration is less after a forecast of good rain than after a forecast of bad rain:

$$M_{1G} < M_{1B} \tag{12}$$

Third, the greater risk taken after a forecast of good weather implies that the difference in harvest between good and bad weather realizations after a forecast of good weather is greater than that difference after a forecast of bad weather. This implies that the difference in harvest season migration in bad and good weather outcomes after a forecast of good weather is greater than that after a forecast of bad weather:

$$M_{bG} - M_{gG} > M_{bB} - M_{gB} \tag{13}$$

Fourth, there is a greater difference between harvest season wages with good and bad weather realizations after a forecast of good weather than after a forecast of bad weather. This is a consequence of the lower planting stage migration, greater planting stage investments and riskier technology choice after a good forecast:

$$\frac{w_{gG}}{w_{bG}} > \frac{w_{gB}}{w_{bB}} \tag{14}$$

Fifth, the wage in the good state of the harvest stage after a forecast of good weather is greater than the wage in the good state of the harvest stage after a forecast of bad weather:

$$w_{gB} < w_{gG} \tag{15}$$

Sixth, all of these results are strengthened as forecast accuracy (q) is improved.

f. Binding Wage Floor. The equilibrium model can be used to assess the consequences of any policies that affect local rural labor markets. We now consider an employment guarantee scheme that provides a prespecified wage and guaranteed work. We do this because in the setting in which we test the model and assess the effects of weather forecasts, rural India, such a scheme was in place, namely the National Rural Employment Guarantee Act (NREGA). The model delivers some novel predictions for how variation in floor wages affects forecast responses as well as equilibrium wages in the harvest and planting stages. To derive these, we use the model to determine how the employment guarantee scheme influences the dynamic choices of cultivators and workers. While such a program cannot reduce the welfare of workers, we will show that it can reduce their wages in some states of nature and even expected worker income. In the latter case, the welfare of cultivators can increase with the guaranteed wage, given the small open village assumption on product markets.

The employment guarantee implies that at the guaranteed wage there might be an excess supply of workers in the community. We assume all of these workers are employed by the institution running the scheme in an activity that generates no output and that the wages are paid from taxpayers who are outside the modeled population. Equilibrium is now defined conditional on the guaranteed wage (w_m) and on the forecast F by a vector of wages $(w_{1F}, w_{gF}, w_{bF}) \equiv w_F$ such that $w_F \geq w_m$ and

$$\begin{gathered} S_{1F}(w_F) \geq x_{1F}(w_F) \; with \; equality \; if \; w_{1F} > w_m \\ S_1\mathcal{F}_1(w_{bF}) + (1 - S_1)\mathcal{F}_2(w_{bF}) \geq \rho x_b(x_{1F}(w_F)) \; with \; equality \; if \; w_{bF} > w_m \\ S_1\mathcal{F}_1(w_{gF}) + (1 - S_1)\mathcal{F}_2(w_{gF}) \geq \rho x_g(x_{1F}(w_F)) \; with \; equality \; if \; w_{gF} > w_m \end{gathered} \tag{16}$$

In appendix 1 we show that regardless of the forecast, an increase in a binding wage floor in any stage/state of production reduces equilibrium wages in at least one other stage/state in which that floor does not bind.

Proposition 2: Suppose that the equilibrium wage vector is $(w_{1F}^*, w_{gF}^*, w_{bF}^*) \equiv w_F^*$ such that $w_F^* \geq w_m$, and $w_F^* \neq w_m$. *Then if a small increase in the statutory minimum wage* w_m *changes the* *equilibrium wage vector, it must reduce the equilibrium wage in at least one state of one stage of production.*

For any forecast F, consider an increase in the minimum wage. If the minimum wage is binding, it must be binding in either the planting stage or in the bad state of the harvest stage (because the wage in the good state of the harvest stage must be no lower than that in the bad state of the harvest stage). Proposition 2 states that if the minimum wage is binding in the planting stage, then an increase in the minimum wage causes equilibrium wages in both the good and the bad states of the harvest stage to decline (unless the minimum wage is also binding in the bad state of the harvest stage, in which case the equilibrium wage in the good state of the harvest stage declines). Similarly, if the minimum wage is binding in the bad state of the harvest stage, then at least one of (w_{1F}, w_{gF}) must decline if the minimum wage is increased.

This result is driven by the complementarity in labor demand between planting and harvest stages (generated by the sequencing of cultivation activities) and by the complementarity in labor supply across planting and harvest stages (caused by the improved distribution of harvest season offers received by early migrants). These joint complementarities imply that a wage increase at one (or several) time or state of nature generates reductions in the demand for labor and increases in the supply of labor that are spread over the entire farming season, causing wages to decline at any other times during the season (or in other states of nature) at which the guarantee is not binding.

It can be the case that the fall in the other two wages is so large that the expected wage over the farming season declines when a binding wage floor is imposed. We show in the appendix that there exist parameters such that $w_{1F} - w_{1F}^{*} + \big(prob(s = g|F)\big)(w_{gF} - w_{gF}^{*}) + \big(1 - prob(s = b|F)\big)(w_{bF} - w_{bF}^{*}) < 0$. For example, expected wages over the season fall when the forecast is for good weather, the skill of the forecast is low, and the gain in the expected harvest season urban wages from planting season migration is high. This configuration of parameters induces a large fall in the planting season wage when the binding wage floor in the bad state of the harvest season increases.

3. IMD Monsoon Forecasts and Forecast Skill

Each year at about the end of June, the Indian Meteorological Department (IMD) in Pune issues forecasts of the deviation of rainfall from "normal" rainfall for the July-September period (summer monsoon). Rainfall in this period accounts for over 70% of rainfall in the crop year and is critical for *kharif*- season profitability - planting takes place principally in June-August, with harvests taking place in September-October. IMD was established in 1886 and the first forecast of summer monsoon rainfall was issued on that date based on seasonal snow falls in the Himalayas. Starting in 1895, forecasts have been based on snow cover in the Himalayas, pre-monsoon weather conditions in India, and pre-monsoon weather conditions over the Indian Ocean and Australia using various statistical techniques.[9] Thus, IMD forecasts are based on information that is unlikely to be known by local farmers. There has been no alternative source of monsoon forecasts other than IMD until 2013, when a private weather services company (Skymet) issued its own forecast for a limited set of regions.

[9] Regression techniques were first used in 1909 to predict monsoon rainfall. IMD has changed statistical techniques periodically, more frequently in recent years. Different statistical methods were used for the 1988-2002, 2003-2006, and 2007-2011 forecasts (Long Range Forecasting in India, undated).

What is the skill of the forecasts in predicting July-September rainfall? The IMD has published the history of its forecasts since 1932 along with the actual percentage deviations of rainfall in the relevant period. One could use the entire time series to assess the forecast. However, in addition to the fact that the statistical modeling has changed over time so that forecast skill in earlier periods may no longer be relevant, the forecast regions have changed - geographical forecasting by region was abandoned in the period 1988-1998 - and in many years the forecasts are qualitative ("far from normal," "slightly below normal"). Starting in 1999, actual percentage deviations were re-introduced. For India as a whole, using the published data from 1999-2010, we find that forecast skill is not very high. However, the forecasts exhibit the symmetry property we have assumed in the model: when the IMD forecast is for below-normal monsoon rainfall or for above-normal monsoon rainfall the likelihood the forecast is correct slightly above 50% in each case.

Forecast skill may, however, vary by region, as India regions differ substantially in rainfall patterns. Indeed, in the period 1999-2003, the forecasts were issued for three regions - Peninsular India, Northwest India and Northeast India. Starting in 2004, the forecasts have been issued for four broad regions of India (see Appendix Map A). To assess area-specific forecast skill, we obtained the correlations between the regional IMD forecasts and village-specific times-series of rainfall in two data sets that contain ground-based (weather station) rainfall data. The first data set is from the ICRISAT Village Dynamics in South Asia (VDSA) surveys from the years 2005-2011 describing farmer behavior in the six villages from the first generation ICRISAT VLS (1975-1984). The villages are located in the states of Maharashtra and Andhra Pradesh. These data contain a module providing daily rainfall for each of the six villages. The second data set we use is from the 2007-8 round of the Rural Economic and Development Surveys (REDS) carried out by the National Council of Economic Research (NCAER). This survey was carried out in 242 villages in the 17 major states of India and includes eight years of monthly rainfall information by village for 212 villages covering the period 1999-2006. For the ICRISAT data (2005-2011) we use the Southern Peninsula and Central forecasts. Table 1 provides the forecasts for the two regions over the period 2009-2014, expressed as the percent of "normal" monsoon rainfall set at 100. For the REDS (1999-2006), we matched up the REDS village rainfall time-series with the appropriate regional forecasts over the time period.

Table 2 provides the correlations between the IMD forecasts and actual July-September rainfall for each of the six ICRISAT villages between 2005 and 2011. As can be seen, for the four Maharashtra villages, skill is relatively high (ρ=.267), but for the two Andhra villages the forecast is not even positively correlated with the rainfall realizations. It is not obvious what accounts for the higher skill in the Maharashtra villages. It is not because there is less rainfall variability in those villages, as the average rainfall CV is significantly higher than that in the Andhra villages. We investigate in more detail below the correlates of forecast skill using the REDS data, given its wider geographic coverage.

That there are regional patterns to forecast skill is also exhibited in the REDS data. While the overall correlation between the forecast and actual July-September rainfall in the 1999-2006 period is only .132, the range in village-specific correlations, where the correlations are non-negative, is from .01 to .77. This variation could just be noise. However, there appear to be broad contiguous geographical areas where the skill is substantially higher. Map 1 shows where in India the correlations are highest (darker areas), with the Northeast area exhibiting the highest skill.

Why should forecast skill differ across regions of India? The major reason is that rainfall distribution characteristics vary spatially such that the correlation in rainfall between regions is imperfect and declines by distance. Thus, if there were to be a perfect annual forecast for one area, the forecast skill would mechanically be less high in other areas. To quantitatively assess the distance-correlation rainfall gradient, we obtained the correlations in monthly rainfall across the 36 geocoded REDS villages in Andhra Pradesh and Uttar Pradesh, resulting in 630 unique distance-correlation pairs. Figure 5 provides the Lowess-smoothed relationship between the monthly rainfall correlations and distance, where the base correlation of rainfall within a village was conservatively set at 0.9. As can be seen the drop-off in the rainfall correlation is steep, falling from 0.9 to less than 0.5 when the inter-village distance exceeds only 100 kilometers.

Figure 5 suggests why there may be region-specificity to forecast skill, but it is not informative about where the skill is highest. For example, forecast skill may be highest where rainfall variability is low. Moreover, whatever the reason for the IMD forecast model to be more skilled in particular regions, when we assess whether the response of farmers and laborers to forecasts varies by skill, we need to consider the possibility that forecast skill is correlated with other local-area characteristics that might affect decisions. For example, it is possible that forecast skill happens to be correlated with better growing conditions, so that farmers are wealthier where skill is high, or forecast skill is greater where particular crops are more suitable, or skill is greater where there is more abundant credit, which permits greater consumption smoothing and facilitates investment. Indeed, we show in Rosenzweig and Udry (forthcoming) based on the ICRISAT data that the response of planting investments to the forecast depends significantly on individual farm soil characteristics.

The first column of Table 3 reports coefficients and their associated standard errors, robust to heteroscedasticity, for a variety of district level characteristics based on a regression in which the dependent variable is a binary indicator for whether or not the average of village-level correlations between the IMD forecasts and actual *kharif*-season rainfall in a REDS district exceeds zero. This correlation is strictly positive in 39 of the 97 REDS districts with complete rainfall data (out of the 100 REDS districts). The specification includes the mean and coefficient of variation of *kharif* rainfall in the district, the fraction of farmer's in the district growing rice, the fraction of villages proximate to a bank, and four district-level average soil characteristics. The set of district characteristics is jointly statistically significant, with the districts having skilled forecasts evidently having higher average rainfall, but not greater rainfall variability, greater access to banks, and greater suitability to growing rice.

When we estimate the responses of farmers and laborers to the monsoon forecasts we will focus on villages and districts where the forecasts have skill. In the third column of Table 3 we report the estimates of the correlates of the district characteristics with the district-level average of village skill for the 39 REDS districts where average skill is strictly positive. In these districts, none of the individual district characteristics are statistically significantly associated with forecast skill, with five of the eight coefficients shrinking substantially in absolute value compared with those estimated from the sample of districts including those with no skill. And for this subsample the full set of coefficients is jointly insignificantly different from zero. While these latter results suggest that the degree of forecast skill, where there is skill, is uncorrelated with potentially important direct determinants of agent decisions we can never measure all of the potential area-specific correlates of skill. The existence of unmeasured area factors correlated with forecast skill is a threat to identification that should be kept in mid in assessing the internal validity of our findings on how forecast skill affects the responses to and outcomes from the forecasts. Because we include individual fixed effects in all our specifications for estimating behavioral responses to the IMD forecasts, however, our estimates of the *average* effects of the forecasts are internally valid for India over the period and in the areas from which the estimates are obtained.

4. Forecasts, Planting-Stage Investments and Farm Profits

a. Farmer risk-taking: planting HYV seeds. . In this section we pin down the value of γ relative to one and quantify the gains to farmers from skilled forecasts. We have shown that, given the consumption-smoothing motive of farmers and their inability to borrow, good-weather farm profits will always be higher than bad-weather profits and a favorable forecast will increase the riskiness of the farmer's choice of planting-stage investments if and only if the farmer's risk aversion (consumption-smoothing motive) is not too strong, specifically if $\gamma < 1$. The model also implies that whatever the sign of the forecast effect on planting-stage investments, the response will be stronger where forecast skill is higher. We first examine the choice of using high-yielding variety (HYV) seeds at the outset of the green revolution, using the Additional Rural Income Survey (ARIS) of NCAER. HYV seeds at the time were substantially more sensitive to rainfall (and fertilizer) than were traditional varieties of the same crops (Foster and Rosenzweig, 1996). Thus, use of HYV seeds at the time unambiguously made the farmer more vulnerable to weather risk. This survey has information on HYV plantings for 2,600 farmers in 250 villages across 100 districts over three years (1968-70) just at the start of the introduction of HYV's.

At the time of the ARIS, the IMD issued monsoon forecasts for only a subset of areas (56 of the 100 districts represented in the sample). The forecasts were qualitative – "normal", "below normal", "much below normal", "above normal". We created a forecast index, coding the most pessimistic forecast as -2, the next pessimistic level as -1, normal as 0. We use the last two years of the panel, so that all farmers had the opportunity to use the technology for at least one year. In the first of the two years, 45 percent of the farmers in the areas where there was a forecast received the most pessimistic forecast, in other areas the forecast was for normal rainfall. In the third year all farmers in forecast areas received a forecast of "below normal' rainfall. Thus, there was variation over the two years in the rainfall forecast for almost half of the sample.

The first column of Table 4 reports the estimates of the IMD forecast on the amount of HYV acreage planted from the two-year panel for farmers in all areas, where we coded the forecast index as zero (for normal) in the areas without a forecast. The second column reports the estimates for the restricted sample of farmers residing in forecast areas. As can be seen the estimates are similar, due to the fact that identification comes only from the change in the forecast, which only occurs in forecast areas. Both indicate that a more favorable forecast increases *R* significantly. The point estimates indicate that change in the forecast from below normal (-1) to normal increases a farmer's planting of HYV acreage by 1.3 acres, which is an increase of 64 percent. This behavior, coupled with the observation (reported below in Table 7) that farmer profits are higher in the good state than in the bad state of the harvest period implies that the risk aversion parameter $\gamma < 1$.

b. Planting-stage investment responses. Given the evidence from farmers' choices of the riskiness of their planting decisions that $\gamma < 1$, we now test the implication of the model that farmers who receive a favorable forecast will increase their planting stage investments. We use two panel data sets. The first is from the expanded ICRISAT Village Dynamics in South Asia (VDSA) surveys from the years 2009-2014 describing the behavior of 3,844 farmers in 20 villages located in six states. A key feature of the data, aside from the availability of daily rainfall for each of the villages, is that, because the data are collected at a high frequency, accurate information is provided on the value of inputs by operation and by date. This enables us to measure *kharif*-season planting-stage investments that are informed by the IMD forecasts (which are issued at the end of June) but made prior to the full realization of rainfall shocks as well as the season-specific profits associated with those investments. These data thus enable us to estimate both response of planting-stage investments to the IMD forecasts as well as the effects of the forecasts and rainfall realizations on farm profits net of farmer fixed effects. Our estimates of the planting-stage investment decisions use an unbalanced panel consisting of 698 farmers appearing in at least two survey years (3,403 observations).

The second panel data set we use is from the 1999 and 2007-8 Rural Economic and Development Surveys (REDS) carried out by the National Council of Economic Research (NCAER). This survey was carried out in 242 villages in the 17 major states of India. Like the ICRISAT survey, this survey elicited information on inputs by season and stage of production in each round so that it is possible to also construct a measure of *kharif* planting-stage investments. While, as noted, the 2007-8 round data also includes monthly rainfall information by village for the years 1999-2006 there is no rainfall information for the year in which profits and inputs were collected in the 2007-8 round, so it is not possible to estimate the effects of rainfall on profits. However, we can use our estimates of forecast skill variation across the 97 districts represented in the data based on the monthly rainfall time-series to assess the responsiveness of investments at the planting stage to the forecasts by skill.

The planting-stage specification is:

$$\ln x_{ijt} = \beta_1 F_{jt} + \beta_2 F_{jt} * q_j + F_{jt} \sum \beta_d Z_{jd} + \lambda_{ij} + \xi_{ijt}, \tag{17}$$

where x_{ijt} = the log of the real rupee value of planting-stage investments for farmer *i* in area *j* at time *t*; F_{jt} = the forecast at time *t* in area *j*, measured as a percent of 100 (normal); q_j = forecast skill in area *j* (average correlation between rainfall and the forecast across the REDS sample villages in the district, with q_j set to zero for district in which the correlation is negative or zero); the Z_{jd} = the area specific correlates of skill in Table 3; λ_{ij} = farmer fixed effect; and ξ_{ijt} = iid error.

The first column of Table 5 reports the estimates of equation (17) based on the REDS panel without the interaction terms containing the skill correlates. As can be seen, at $q_j = 0$ (no skill) there is no relationship between the forecast and planting-stage investment, but at skill levels above zero a forecast of good rainfall increases planting investments. The point estimate of the skill/forecast interaction coefficient suggests that at the mean correlation across the 39 districts with skill (0.316), a one percentage point increase in the forecast value would increase planting-stage investments by 5.2 percent. Adding the forecast interaction terms with the area variables in columns two and three does not substantially alter the skill/forecast interaction coefficient. And the complete set of area/forecast interaction coefficients are not statistically significant. The results indicating that farmers respond positively to forecasts of good weather in skill areas appears robust to at least a wide variety of climate and soil and credit correlates, and are consistent with $\gamma < 1$.

Column one of Table 6 reports the estimate of the effect of the IMD weather forecast on planting-stage investments in the set of ICRISAT villages. Here too, the average response to an increase in the optimism of the forecast is positive. However, the sample contains the villagers in the Andhra

Pradesh where the forecast has no skill. In column two therefore we allow the investment forecast response to differ across the farmers in the Andhra villages and the rest of the sample (the Z's in equation (17) are replaced by the Andhra dummy). As can be seen, in the skilled villages the investment response is statistically significantly higher than that in the villages of Andhra Pradesh. The point estimates indicate that in the non-Andhra villages for every percentage point increase in the forecast value, planting-stage investment rise by 3.2 percent; in the Andhra villages, investments rise by a statistically insignificant .65 percent. Finally, in columns three and four in Table 6 we replace the linear forecast variable by a dummy variable indicating a "bad" forecast - whether the forecast value was less than 98 (98% of normal rainfall) - which is observed in approximately half the sample-period values. The effects of having this pessimistic forecast is to lower planting-stage investments by 15.8 percent overall, and by over 18 percent in the skill villages, compared with only 4.4 percent in the Andhra villages.

c. Rainfall, rainfall forecasts and farm profits. In this section we assess the profitability of accurate rainfall forecasts and further verify that that $\gamma < 1$. The responsiveness of farm profits to rainfall is an important dimension of the economic environment. The model implies that if farm profits are higher when seasonal rainfall is higher, and $R_G > R_B$, as we have seen, then we can conclude that $\gamma < 1$. We use the ICRISAT panel of farmers in the non-Andhra villages where the forecast has skill and farmer investments evidently respond to forecasts. The number of farmers with at least two observations in these villages is 557. Our measure of profits is the real value of agricultural output minus the value of all agricultural inputs, including the value of family labor and other owned input services.[10] As before when we assessed forecast skill, we use the total amount of rainfall in the *kharif* period as our measure of rainfall. The first column of Table 7 reports the estimates of seasonal rainfall on profits in a quadratic specification. For all values of *kharif* rainfall observed in the data, the effect of rainfall on profits is positive and statistically significant. Thus, the profit, risk-taking and investment estimates are consistent with $\gamma < 1$.

Given the forecasts and realized rainfall over the period we can quantify the average gains to farmers from having correct forecasts (at the sample skill level) over the sample period – the profitability of forecasts. The key advantage that the forecast provides is that it allows farmers to exploit the gains from higher rainfall and to minimize the losses from lower rainfall. We have seen that indeed farmers invest more and take more risk when there is an optimistic forecast. We should therefore observe that when there is a good forecast, increases in rainfall increase profits more than when there is a bad forecast, and symmetrically, when rainfall declines, the loss in profits is less when there was a pessimistic forecast compared with a forecast of normal weather.

To test whether we in fact observe significant gains from the forecasts, we add in the second column of Table 7 interactions between the two rainfall variables and the dummy variable indicating whether the forecast value was less than 98. The squared rainfall/forecast interaction term is highly statistically significant, and is negative – when the forecast is bad, the positive effect of rainfall is

[10] Our model suggests that the value of output should be discounted by r, the return on risk-free assets between the time of input application and the time of harvest. Appendix Table A shows the nominal annual interest rates of formal and informal savings accounts held by the ICRISAT households. 85% of the households have positive savings balances. The average nominal interest rate (weighted by value of deposit) is 10.4%. Average annual inflation over the span of the ICRISAT survey was 10.6%. Therefore, we set r=1 and do not discount output when we calculate profits.

attenuated, as farmers invest less and more conservatively. To quantify the gains, we computed the derivatives of the rainfall effects on profits at mean rainfall when there is a forecast of good weather and when there is a forecast of bad weather. These derivatives and their associated standard errors are also reported in the second column of the table. The estimates indicate that when the forecast is good, on average profits increase by 37 rupees for every millimeter increase in realized rain, and when the forecast is bad, the rate of profit decrease when rainfall declines by one millimeter is only 29 rupees. The difference across the two forecast effects of 8 rupees per millimeter of rain is statistically significant and is the net gain from having correct forecasts, at the level of skill and thus investment/risk-taking responsiveness in the sample. This suggests that if in a bad monsoon rainfall is lower by one-half a standard deviation and in a good monsoon it is higher by one-half a standard deviation profits are increased by 11.5 percent when forecasts are correct. Of course, if the forecasts are incorrect, this is the loss. The net gain is from the forecasts being correct more than half the time – thus, the greater the forecast skill the greater the gain, even ignoring that increases in forecast skill also amplify farmers' responses, as we have seen, and thus also increase the net gain. Given that there are 118.7 million farmers in India (2011 India census), the 11.5% increase in profitability from a correct forecast, if the same level of average forecast skill observed in the ICRISAT villages applied to all of India and using the mean profits of the ICRISAT farmers in 2011 rupees as the base, implies a total gain of 29.1 billion rupees accruing to farmers, with little administrative costs of delivery.

5. Forecasts, Minimum Wages and Planting-Stage Worker Out-migration

Our estimates from the sample of farmers indicated that forecasts affect farmer investments and risk-taking, the more so the greater is forecast skill, and farmers benefit from greater forecast skill in the form of higher profits. The effects of forecasts on worker wages, however, depends also on what happens to worker supply, on worker migration responses. Our estimates of farmer behavior, consistent with the model, indicate that a pessimistic forecast decreases worker demand in the planting period, which should lower planting-stage wages in equilibrium. However, the model also suggests that pessimistic forecasts increase out-migration, and thus lower supply. The net effect on worker wages in the planting stage is theoretically ambiguous. In this section we estimate the forecast response of worker out-migration immediately after the rainfall forecast. Specifically, we estimate the probability that a male worker leaves the village for work in July and August. We use two data sets, a panel of workers from the 2010-2014 rounds of the ICRISAT data in the villages outside of Andhra Pradesh and a panel of districts from four rounds (62, 63, 64, 66) of the National Social Survey (NSS), covering the periods 2005-2007 and 2009. During this period, we need to take into account the NREGA (real) guaranteed minimum wages that were in effect. The model implies that where the wages are higher, out-migration is lower and that higher minimum wages blunt the effects of the forecast on out-migration. Thus, we merged in each data the state-and year-specific real statutory minimum wages associated with the NREGA program.

We first obtain estimates from a panel of males aged 19-49 from the 2010-2014 rounds of the ICRISAT data in the villages outside of Andhra Pradesh. The specification we estimate is:

$$s_{ijt} = \alpha_1 F_{jt} + \alpha_2 \omega_{jt} + \alpha_3 F_{jt}\omega_{jt} + \lambda_{ij} + \xi_{ijt}, \tag{18}$$

where S_{ijt} = 1 if a male worker *i* aged 19-49 residing in area *j* is located outside the village in year *t* in the months of July and August; F_{jt} = 1 if the forecast value is below 98 (low rainfall); ω_{jt} is the real statutory minimum wage associated with NREGA in area *j* at time *t*; λ_{ij} = worker fixed effect; and ξ_{ijt} = iid error. The model predicts that $\alpha_1 > 0$ and $\alpha_3 < 0$.

The first column of Table 8 reports the estimates from a specification that omits the interaction between the minimum wage and the forecast. The estimates indicate that, consistent with the model, a pessimistic forecast increases out-migration, by 2.4 percentage points, a 37 percent increase at the sample mean out-migration rate (6.4 percent). On average across the period a higher minimum wage lowered out-migration. However, while the minimum wage effect is statistically different from zero, it is small – a one standard deviation increase in the wage decreases out-migration by only 0.8 percentage points. However, as is seen in the second column of Table 8 in which the interaction between the forecast and the minimum wage is included, the inhibiting minimum wage effect on out-migration is significantly higher in absolute value when there is a pessimistic forecast, consistent with the model. The estimates indicate that when the forecast is not pessimistic, there is no significant effect of a rise in the minimum wage on out-migration, but when the forecast is pessimistic a one standard deviation increase in the real minimum wage decreases out-migration by 1.5 percentage points (23 percent). The forecast effect on out-migration is also reduced significantly – when the forecast is pessimistic, a one-standard deviation increase in the minimum wage lowers the positive effect of the forecast on out-migration by 64 percent.

As noted, the limited geographic coverage of the ICRISAT survey prevents examining how forecast skill affects forecast responsiveness. The NSS has national coverage and thus we can exploit the geographic variation across India in forecast skill that we obtained using the REDS data. Selected rounds of the NSS contain information on temporary migration in Schedule 1.0, which ascertains the number of days away from home in the last month. Because the NSS collects information in every month of the year, we can look at July/August planting-stage out-migration using the rounds administered in August and September. We use data on male agricultural workers in rural areas who are residing in the districts common with those in the REDS data set. We thus merge the estimates of skill obtained from the REDS data with the NSS worker data to assess if forecast skill matters for migration decisions.

There are two main limitations of the NSS for our analysis. The first is that the NSS is not a panel of individuals or households. It is panel of administrative units that are larger than villages but smaller than districts. We thus need to control for both time-invariant worker characteristics and the agroclimatic characteristics of the villages. The second limitation of the NSS data is that there is no rainfall information. We thus merge TRMM satellite data on rainfall over the relevant periods to the NSS data at the village level. Comparisons of the time-series of the village-matched TRMM data with the REDS and ICRISAT ground-based rainfall indicate that the satellite matching is not very accurate. We only use the first two moments of the TRMM rainfall data as village-level control variables. The distribution of moments of the TRMM and ground-based rainfall time-series are substantially more correlated at the village-level than are the year-to-year values.

The specification we use for estimation is:

$$s_{ijt} = \alpha_1 F_{jt} + \alpha_2 F_{jt} q_j + \alpha_3 \omega_{jt} + \alpha_4 F_{jt} \omega_{jt} + \alpha_5 F_{jt} \omega_{jt} q_j + \alpha_6 Z_{ijt} + \mu_j + \xi_{ijt}, \tag{19}$$

where s_{ijt} = 1 if a male agricultural worker *i* aged 14-49 residing in area *j* is in located outside the village in year *t* in the months of July and August; F_{jt} = the forecast at time *t* in area *j*, measured as whether the forecast value is below 98 (low rainfall); ω_{jt}= the real statutory minimum wage associated with NREGA in area *j* at time *t*; q_j = forecast skill in area *j* (average correlation between rainfall and the forecast across the REDS sample villages in the district, set to zero if < 0); μ_j= area fixed effect; and ξ_{ijt} = iid error. We also include in the specification as controls Z_{ijt}, which includes the worker's schooling, age and age squared, the household's landholdings, and the mean and standard deviation of rainfall in the worker's village. The model predicts that $\alpha_2 < 0$ and $\alpha_5 < 0$.

The first column of Table 9 reports the estimates of the determinants of planting-stage out-migration omitting the interaction variables. The estimates show that a forecast of bad weather, just as in the ICRISAT sample, significantly increases out-migration in the planting stage, the more so the greater the skill of the forecast. At the sample mean skill for districts with skill (.224) the point estimates indicate that a bad forecast increases planting-stage migration by 20 percentage points, a 54 percent reduction in out-migration. On average the effect of the minimum wage over the period was not statistically significantly different from zero. However, as seen in column two of the table, a higher minimum wage significantly reduces out-migration in the planting stage when the forecast predicts low monsoon rainfall (only) when the forecast has skill, again consistent with the model. The point estimates indicate that at the mean skill, an increase in the minimum wage by one standard deviation reduces out-migration by 23.5 percentage points (64 percent) when the forecast indicates low monsoon rainfall.

6. Forecasts, Minimum Wages and Equilibrium Planting-stage Wages

The estimates of the effects of a bad forecast on planting-stage farmer investments suggests that such forecasts reduce the demand for labor in the planting stage and thus would lower equilibrium wages. However, also consistent with the model, forecasts of low rainfall induce greater out-migration in the planting stage, which would raise planting-stage wages. The net effect on equilibrium planting-stage wages resulting from a pessimistic forecast is thus an empirical question. In this section we estimate the effects of the forecast on equilibrium wages in the planting stage. Given our theoretically-consistent finding that a higher minimum wage inhibits the migration response to forecasts, we also test whether higher minimum wages lower equilibrium wages in the planting stage when rain shortfalls are forecast. We again use the sample of male workers from the ICRISAT panel survey residing outside of Andhra Pradesh and the sample of men in the NSS data.

The first column of Table 10 reports the worker fixed-effects estimates of the effects of a bad forecast on the log of agricultural wages in the planting stage for the ICRISAT sample of male workers aged 19-49 along with the estimate of the effect of the statutory minimum wage. The estimates indicate that on net a bad forecast raises wages in the planting stage – the migration/supply response evidently dominates such that wages are 5.7 percent higher when there is a pessimistic forecast. And, on average, higher minimum wages are associated with higher equilibrium planting stage wages. However, as the estimates in the second column of Table 10 indicate, the net effect of a rise in the minimum wage on the equilibrium wage in the planting stage when there is a bad forecast is negative. A one-standard deviation in the real minimum wage decreases the planting-stage equilibrium wage by almost 3.7 percent when the forecast suggests a low-rainfall *kharif* season.

The estimates from the NSS data for equilibrium planting-stage wages are somewhat different from those from the ICRISAT data in areas where the forecast has skill. In the second-column of Table 11, which contains estimates from the full specification, the forecast of bad weather and its interaction with the real minimum wage are both statistically different from zero. The point estimates indicate that at the mean real minimum wage and average skill in the skill areas, a pessimistic forecast lowers equilibrium planting-stage wages, but only by 2.1 percent. However, as also found in the ICRISAT survey data, a rise in the minimum wage when the forecast is bad lowers the equilibrium planting-stage wage. The point estimates indicate that a one-standard-deviation increase in the minimum wage would lower the equilibrium wage in the planting stage by 4.7 percent, a result similar in magnitude to that obtained from the ICRISAT data.

7. Forecasts, Rainfall, Minimum Wages and Equilibrium Harvest-stage Outcomes

Planting-stage migration decisions are made prior to the realization of rainfall based on expectations of subsequent rainfall, which are evidently influenced by the IMD forecast. Harvest-stage migration in contrast occurs after the realization of rainfall and thus is not only affected by the planting-stage forecast (due to its effects on planting-stage migration and the planting decisions of farmers) but also by the realizations of rainfall. Harvest-stage equilibrium wages are also affected by both rainfall outcomes and the forecast. Higher rainfall increases output and thus raises labor demand, and in equilibrium, despite higher rainfall lowering out-migration, raises equilibrium wages. However, the key insights of the model are that the effects of any determinant of harvest-stage migration and wages are affected by the rainfall forecast – rainfall as well as minimum wages interact with the forecast. In particular, when the forecast of rainfall was pessimistic, the effects of changes in rainfall and the minimum wage on out-migration and wages are attenuated compared with states of the world in which the forecast is optimistic. And, as we have shown, it is theoretically possible that when there is a bad forecast but normal rainfall a higher minimum wage can lower harvest-stage equilibrium wages.

In this section we test the implications of the model for the determination of harvest-stage out-migration and equilibrium wages. Because rainfall is a key determinant of harvest-stage outcomes, we obtain estimates from the ICRISAT panel of workers, making use of the village-level daily rainfall information contained in the survey. We again focus on the workers in the villages outside of Andhra Pradesh, where the IMD forecast has skill. The equation we estimate is:

$$y_{ijt} = \pi_1 F_{jt} + \pi_2 \omega_{jt} + \pi_3 r_{jt} + \pi_4 F_{jt}\omega_{jt} + \pi_5 F_{jt} r_{jt} + \lambda_{ij} + \xi_{ijt}, \tag{20}$$

where $y_{ijt} = 1$ if a male worker *i* aged 19-49 residing in area *j* is in located outside the village in year *t* in the months of September and October or the log of the real daily wage in those months; $F_{ijt} = 1$ if the forecast at time *t* in area *j* is below 98 (low rainfall); ω_{jt}= the real statutory minimum wage associated with NREGA in area *j* at time *t*; r_{jt} = rainfall in the months of July through September; λ_{ij} = worker fixed effect; and ξ_{ijt} = iid error. The model predicts that for migration $\pi_1 > 0, \pi_2, \pi_3 < 0, \pi_4, \pi_5 > 0$. For equilibrium wages, the signs are opposite to those for migration: $\pi_1 < 0, \pi_2, \pi_3 > 0, \pi_4, \pi_5 < 0$.

The first column of Table 12 reports the coefficients for the rainfall, forecast and minimum wage variables omitting the interaction terms in the equation determining harvest-stage out-migration. Consistent with the model, migration at the harvest stage is lower when rainfall and the minimum wage are higher but out-migration is higher when the planting-stage forecast was pessimistic. All coefficients are statistically significant. In the second column the interaction terms are added. All three interaction coefficients are statistically significant from zero. Consistent with the model, the positive effect of a bad forecast on out-migration is significantly decreased at higher values of the statutory minimum wage. The point estimates indicate that at the sample mean values of rainfall and the real minimum wage, a bad forecast increases harvest-stage migration by a statistically significant 35.6 percent; but when the minimum wage is one standard deviation higher, the same forecast only reduces out-migration in the harvest stage by a statistically insignificant 5.3 percent. On the other hand, a rise in the minimum wage of one standard deviation at the sample means when there is a forecast of good weather reduces harvest-stage out-migration at sample mean rainfall by only 5.4 percent but reduces harvest-stage out-migration by 24.6 percent if there was a pessimistic forecast. The only coefficient that deviates from the model predictions is that for the interaction between the forecast and rainfall, which suggests that rainfall has a stronger negative effect on harvest-stage out-migration when the forecast was for reduced rainfall.

The results in Table 12 permit us to calculate a lower bound to the gain that workers receive from a correct forecast. We show in the Appendix that, abstracting from the effect of forecasts on equilibrium wages, the gain in expected annual earnings of a landless worker from having a correct forecast is equal to

$$\frac{1}{4}(M_{1B} - M_{1G})\left((M_{gB} - M_{gG})w_{gF} - (M_{bB} - M_{bG})w_{bF}\right) \tag{21}$$

Planting stage migration probabilities after bad and good forecasts are taken from column 1 of Table 9; the differences in migration rates in the harvest stage in good and bad states, after good and bad forecasts are drawn from column 2 of Table 12 (using a one standard deviation increase in rain as the gap between good and bad season rainfall). The good and bad harvest stage wages are calculated using a base bad harvest stage log wage of 7.39, which is the 25th percentile of the harvest wage distribution, along with the coefficient on rainfall from column 1 of Table 13. The expected gain from a correct forecast to a migrant in the ICRISAT sample is small, because the skill of forecasts in the ICRISAT sample is low, implying a very small difference in migration patterns by forecast. ICRISAT migrants gain Rs. 25, on average, from a correct forecast. Since only 2.35% of landless workers change their migration decisions based on the forecast, the overall value of a correct forecast to the 105 million casual workers across India is Rs. 61 million. This is a lower bound estimate. We have shown that as forecast skill increases, planting stage migration responsiveness to forecasts increases, and the gain to a correct forecast rises accordingly. And the existence of NREGA, which provides a wage floor for stayers, also reduces the responsiveness of migration to forecasts.

In contrast to the results for out-migration, all of the estimated coefficients of the log wage equation conform to the predictions of the model. The estimates are reported in Table 13. In the first column, as predicted, higher rainfall and a forecast of a poor monsoon raise harvest wages as do higher minimum wages on average. As seen in column two, all of the interaction coefficients are statistically significant. In accordance with the model, real harvest-stage wages rise less with rainfall if there was a pessimistic forecast and in areas where minimum wages are higher. And the positive effect of a rise in the minimum wage on equilibrium harvest wages is less when the forecast predicted a bad monsoon.

Indeed, the point estimates in the second column of the table indicate that a rise in the minimum wage can reduce the harvest equilibrium wage when the forecast is pessimistic as suggested by the model. In particular, when the forecast predicts a normal or better monsoon, at average *kharif* rainfall levels, a one standard deviation increase in the minimum wage pushes up equilibrium harvest-stage wages by a statistically significant 10.9 percent. However, when the forecast was for a bad monsoon, the same rise in the minimum wage under the same (normal) realized rainfall conditions lowers harvest wages by a statistically significant 5.5 percent. As indicated by the model, this occurs when actual rainfall is normal and the minimum wage is binding in the planting stage but not the harvest stage. The binding minimum wage together with the (incorrect) pessimistic forecast reduce farmer investments and increase the supply of local workers, both of which lower the harvest wage in equilibrium when the minimum wage is not binding in that stage. Note that the estimates suggest that if realized rainfall is at its sample low and the forecast is pessimistic (and thus correct), a rise in the minimum wage still raises equilibrium wages, by a marginally statistically significant 2.8 percent. The perverse effect of the minimum wage on equilibrium wages is thus due to an inaccurate forecast; increasing forecast skill would thus reduce the incidence of cases in which workers in the harvest stage are harmed by increases in the minimum wage (combined with guaranteed employment).

8. Conclusion

In this paper we have set out a parsimonious dynamic equilibrium model of rural economies in low-income countries that incorporates a number of their fundamental properties: the importance of agriculture and its sequential decision-making, the role of temporary migration, the salience of weather risk, and the necessity of decision making by both laborers and farmers prior to the resolution of uncertainty. We used the model as a framework to assess empirically, based on panel data from India, the effects of long-range weather forecasting in the presence of variable weather outcomes and a guaranteed-employment minimum-wage scheme on the input and technology choices of farmers, the migration decisions of laborers, farm profits and equilibrium wages in the planting stage and at harvest.

We first showed, using ground-level times-series data on monthly rainfall at a fine geographical resolution across India, that the monsoon forecasts issued by the India Meteorological Department in recent years exhibited skill only in a few contiguous regions in India. Our empirical results, examining investments and migration decision as well as profits and wages, indicated that only in areas in which the forecasts were skillful, did the forecast significantly affect outcomes. Moreover, within the skill areas, the higher the skill level of the forecasts, the greater its effects. Where the forecast effects were salient, we found that they were aligned with the predictions of the model: favorable rainfall forecasts lead to a higher level and risker planting-stage investments by farmers, lower rates of planting-stage out-migration migration, and lower equilibrium wages in the planting stage. We showed that the forecasts in particular raised farm profits on average by allowing farmers to allocate resources *ex ante* to exploit rainfall conditions.

The effects of weather forecasts on equilibrium wages in the harvest stage were more complex, depending on both rainfall outcomes, the level of minimum wages, and whether the forecast was pessimistic or optimistic. For example, harvest stage out-migration and wages were more sensitive to rainfall outcomes when the rainfall forecast was favorable compared to when it was unfavorable. And, in areas with higher minimum wages, responses to weather outcomes and to the forecast were less strong, with average equilibrium wages actually lower in high minimum-wage areas if the forecast was pessimistic.

Our results suggest that expected improvements in long-run weather forecasting skill will have economically significant beneficial effects for rural populations, while avoiding the administrative costs of delivering traditional contract-based services to the poor that rely on personal interventions. Our estimates from an area in India where the forecasts have some skill and farmers and landless laborers respond to the forecasts indicate, if that level of forecast skill were applicable to all of India, that the expected total gains from a correct forecast would be over 29 billion rupees, a small part of which also benefits the landless. Our results also imply that any evaluations of interventions in rural areas in India, such as NREGA, need to take into account the specific forecasts in place as well as realized weather outcomes at the time of the interventions to maximize external validity. Finally, our model ignored networking among rural agents. The integration of dynamic equilibrium elements incorporating forecasts and production decisions in network models would appear to be a fruitful agenda for future research.

References

Balmaseda, M. Y. Fujii, O. Alves, T. Lee, M. Rienecker, T. Rosati, D. Stammer, Y. Xue, H. Freeland, M. J. McPhaden, L. Goddard, and C. Coelho. (2009). “Role of the ocean observing system in an end-to-end seasonal forecasting system.” In J. Hall, D. E. Harrison, and D. Stammer, eds. *Proceedings of OceanObs’09: Sustained Ocean Observations and Information for Society* (Vol. 2), Venice, Italy, ESA Publication WPP-306, p. 21-25.

Banerjee, Abhijit, Dean Karlan, and Jonathan Zinman. 2015. “Six Randomized Evaluations of Microcredit: Introduction and Further Steps.” *American Economic Journal: Applied Economics* 7 (1): 1–21.

Berg, E., S. Bhattacharyya, R. Durgam, and M. Ramachandra (2013). “Can Rural Public Employment Schemes Increase Equilibrium Wages? Evidence from a Natural Experiment in India.” Mimeo.

Bryan, Gharad, Shyamal Chowdhury and Ahmed Mushfiq Mobarak (2014). “Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh.” *Econometrica* 82 (5), p. 1671-1748.

Carter, Michael, Alain de Janvry, Elisabeth Sadoulet, and Alexandros Sarris. 2017. “Index Insurance for Developing Country Agriculture: A Reassessment.” *Annual Review of Resource Economics* 9 (1): 421–38.

Cole, Shawn A., and Wentao Xiong. 2017. “Agricultural Insurance and Economic Development.” *Annual Review of Economics* 9 (1): 235–62.

Dupas, Pascaline, and Jonathan Robinson. 2013. “Why Don’t the Poor Save More? Evidence from Health Savings Experiments.” *American Economic Review* 103 (4): 1138–71.

Ghosal, Sutanaku and Rituraj Tiwari Kolkata, (2012). “With Villainous Forecasts, MET a Fair-Weather Friend” *Times of India*. http://epaper.timesofindia.com/Default/Scripting/ArticleWin.asp?From=Archive&Source=Page&Skin=ETNEW&BaseHref=ETD/2012/07/25&PageLabel=1&EntityId=Ar00102&ViewMode=HTML

Imbert, Clément, and John Papp. (2015). "Labor Market Effects of Social Programs: Evidence from India's Employment Guarantee." *American Economic Journal: Applied Economics* 7 (2): 233-63.

Ingram, K. T, M. C Roncoli, and P. H Kirshen. 2002. “Opportunities and Constraints for Farmers of West Africa to Use Seasonal Precipitation Forecasts with Burkina Faso as a Case Study.” *Agricultural Systems* 74 (3): 331–49.

Jones, J. W., J. W. Hansen, F. S. Royce, and C. D. Messina. 2000. "Potential Benefits of Climate Forecasting to Agriculture." *Agriculture, Ecosystems & Environment* 82 (1): 169–84.

Jensen, Robert (2007). "The Digital Provide: Information (Technology), Market Performance and Welfare in the South Indian Fisheries Sector," *Quarterly Journal of Economics*, 122(3), p. 879 - 924.

Karlan, Dean, Isaac Osei-Akoto, Robert Osei, and Chris Udry (2014). "Agricultural Decisions after Relaxing Credit and Risk Constraints," *Quarterly Journal of Economics*, 129(2): 597-652.

Mase, Amber Saylor, and Linda Stalker Prokopy. 2013. "Unrealized Potential: A Review of Perceptions and Use of Weather and Climate Information in Agricultural Decision Making." *Weather, Climate, and Society* 6 (1): 47–61.

Meghir, Costas, Mushfiq Mobarak, Corina Mommaerts, and Melanie Morten. (2017). "Migration and Consumption Insurance in Bangladesh." Mimeo.

Meza, Francisco J., James W. Hansen, and Daniel Osgood. 2008. "Economic Value of Seasonal Climate Forecasts for Agriculture: Review of Ex-Ante Assessments and Recommendations for Future Research." *Journal of Applied Meteorology and Climatology* 47 (5): 1269–86.

Mjelde, James W., Steven T. Sonka, Bruce L. Dixon, and Peter J. Lamb. 1988. "Valuing Forecast Characteristics in a Dynamic Agricultural Production System." *American Journal of Agricultural Economics* 70 (3): 674–84.

Morten, Melanie (2019), "Temporary Migration and Endogenous Risk Sharing in Village India," Journal of Political Economy 127 (1), p. 1-46.

Mobarak, Ahmed Mushfiq and Mark Rosenzweig (2014). "Risk, Insurance and Wages in General Equilibrium." NBER Working Paper No. 19811.

National Research Council (2010). *Assessment of Intraseasonal to Interannual Climate Prediction and Predictability*. Washington, DC: The National Academies Press.

Nesheim, Ingrid, Line Barkved, and Neha Bharti. 2017. "What Is the Role of Agro-Met Information Services in Farmer Decision-Making? Uptake and Decision-Making Context among Farmers within Three Case Study Villages in Maharashtra, India." *Agriculture* 7 (8): 70.

Patt, Anthony, and Chiedza Gwata. 2002. "Effective Seasonal Climate Forecast Applications: Examining Constraints for Subsistence Farmers in Zimbabwe." *Global Environmental Change* 12 (3): 185–95.

Roncoli, Carla. 2006. "Ethnographic and Participatory Approaches to Research on Farmers' Responses to Climate Predictions." *Climate Research* 33 (1): 81–99.

Rosenzweig, Mark and Christopher Udry (forthcoming). "External Validity in a Stochastic World: Evidence from Low-Income Countries." *Review of Economic Studies*.

Santangelo, Gabriella (2019). "Firms and Farms: The Local Effects of Farm Income on Firms' Demand."

Stockdale, T. N. D. L. T. Anderson, M. A. Balmaseda, F. Doblas-Reyes, L. Ferranti, K. Mogensen, T. N. Palmer, F. Molteni, and F. Vitart. (2010). "ECMWF Seasonal Forecast System 3 and its prediction of sea surface temperature." *Climate Dynamics* (in review).

Suri, Tavneet and William Jack (2016). "The Long-run Poverty and Gender Impacts of Mobile Money." Science 09 (354). Issue 6317, p. 1288-1292.

Takahashi, Kazushi, Christopher B. Barrett, and Munenobu Ikegami. 2019. "Does Index Insurance Crowd In or Crowd Out Informal Risk Sharing? Evidence from Rural Ethiopia." *American Journal of Agricultural Economics* 101 (3): 672–91.

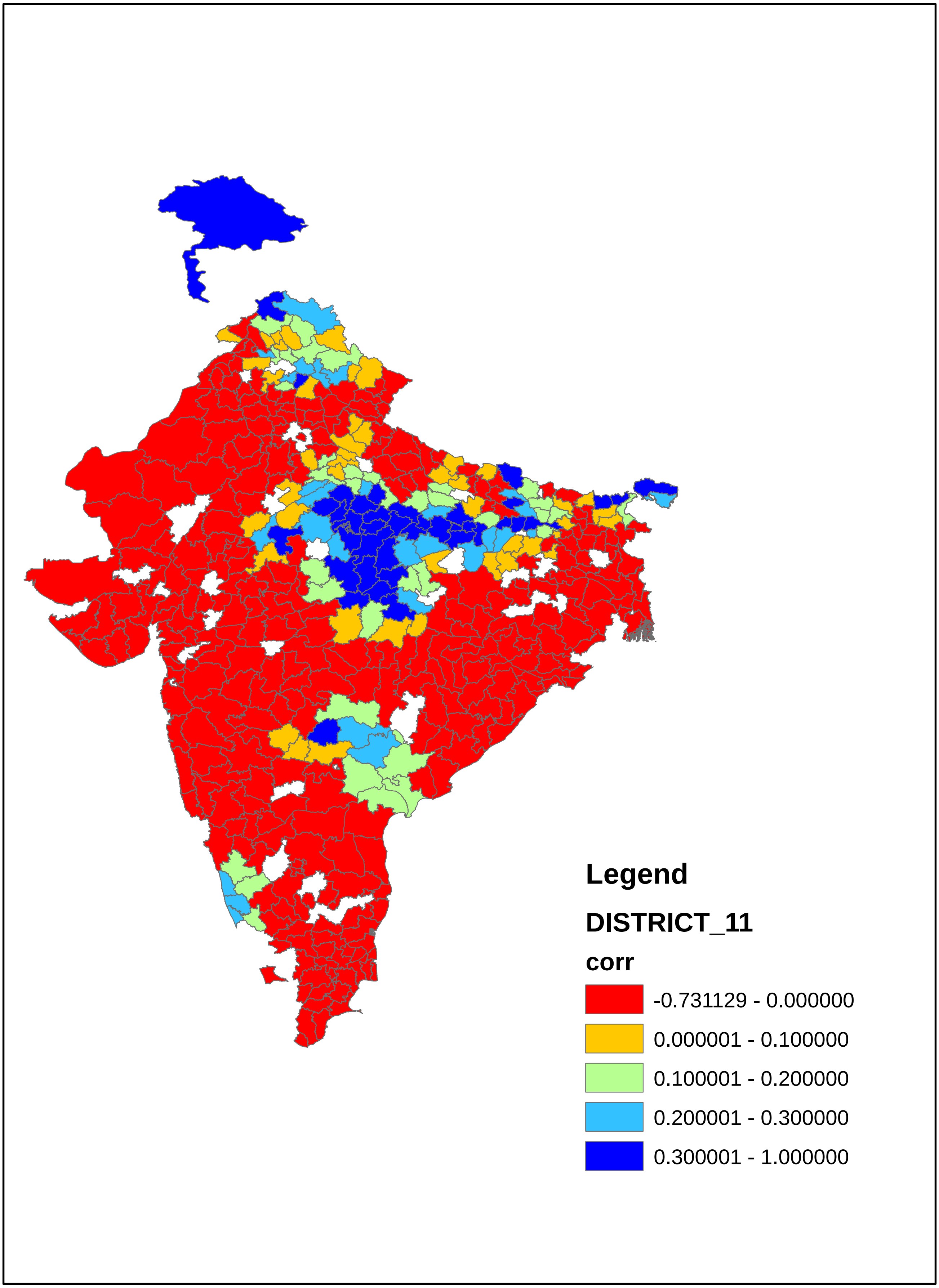

Legend
DISTRICT_11
corr
-0.731129 - 0.000000
0.000001 - 0.100000
0.100001 - 0.200000
0.200001 - 0.300000
0.300001 - 1.000000

Figure 1. Percent Change in the India National Stock Exchange Fifty, by Event (2013-2017)

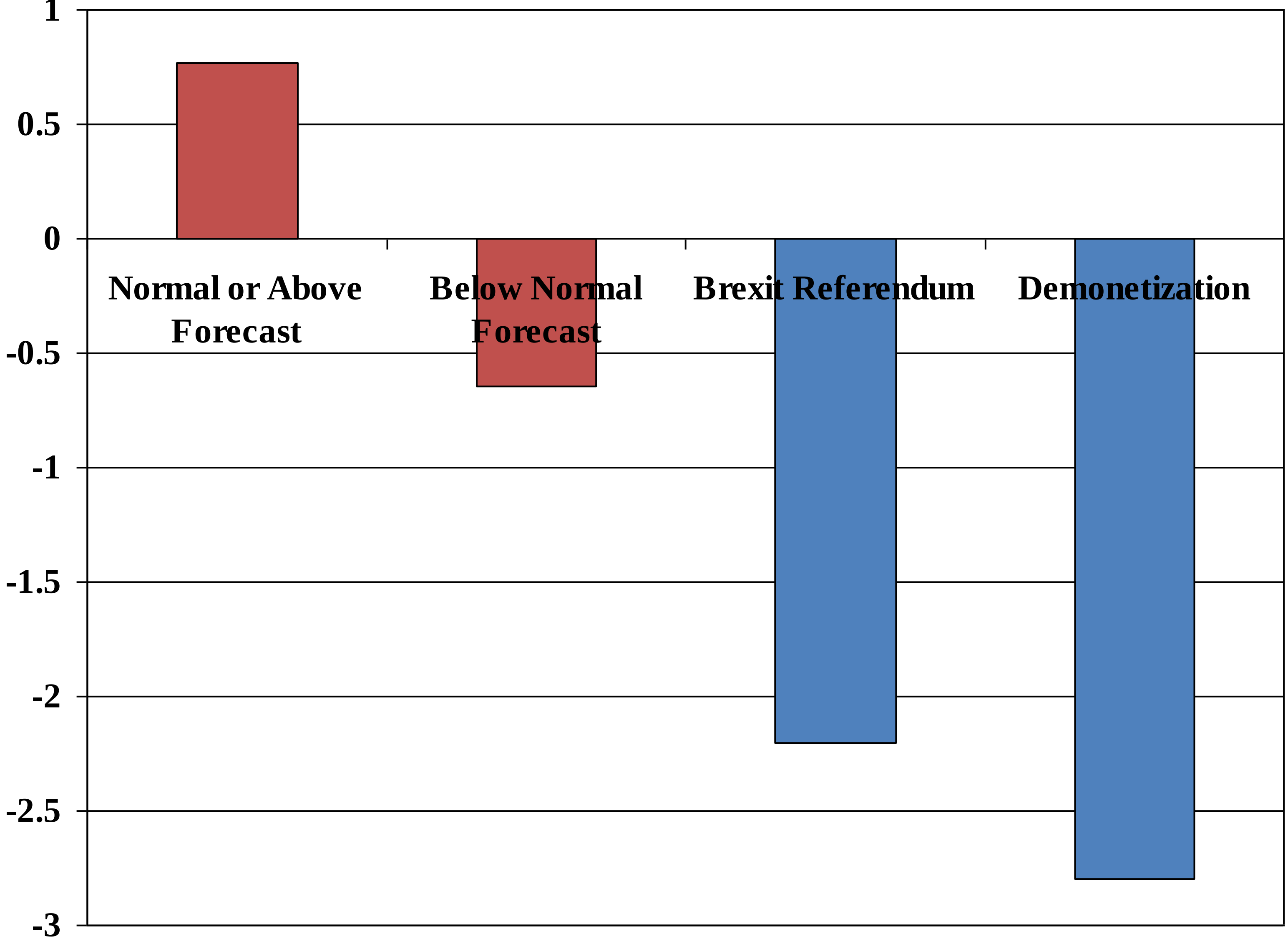


Figure 2. Proportion of Rural Workers in Urban Areas Among Men Aged 19-49, by Month (Source: ICRISAT VLS 2010-2014)

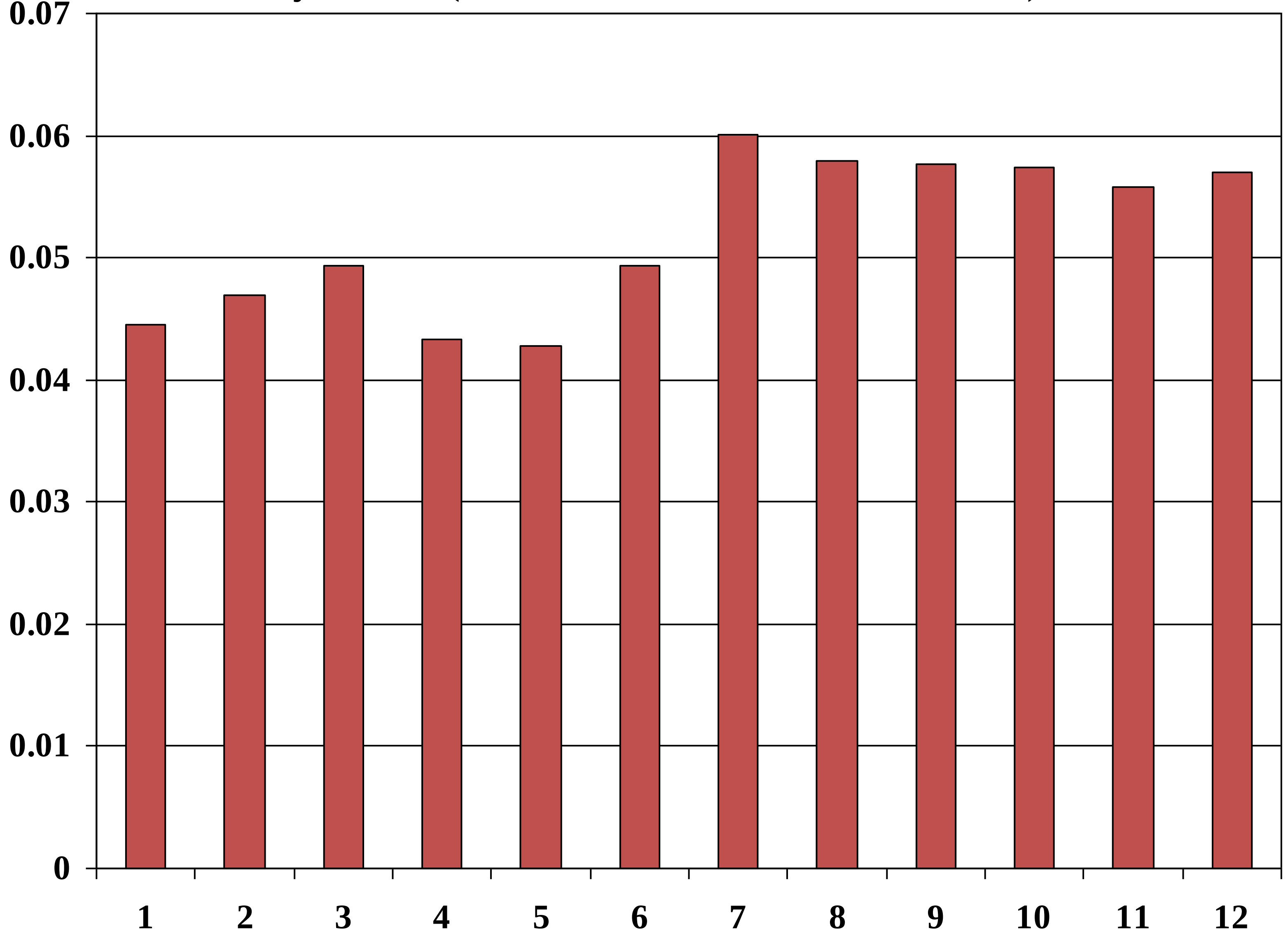


Figure 3. Proportion of Rural Workers Away from Home Among Men Aged 19-49, by Month (Source: NSS Round 66, 2009/10)

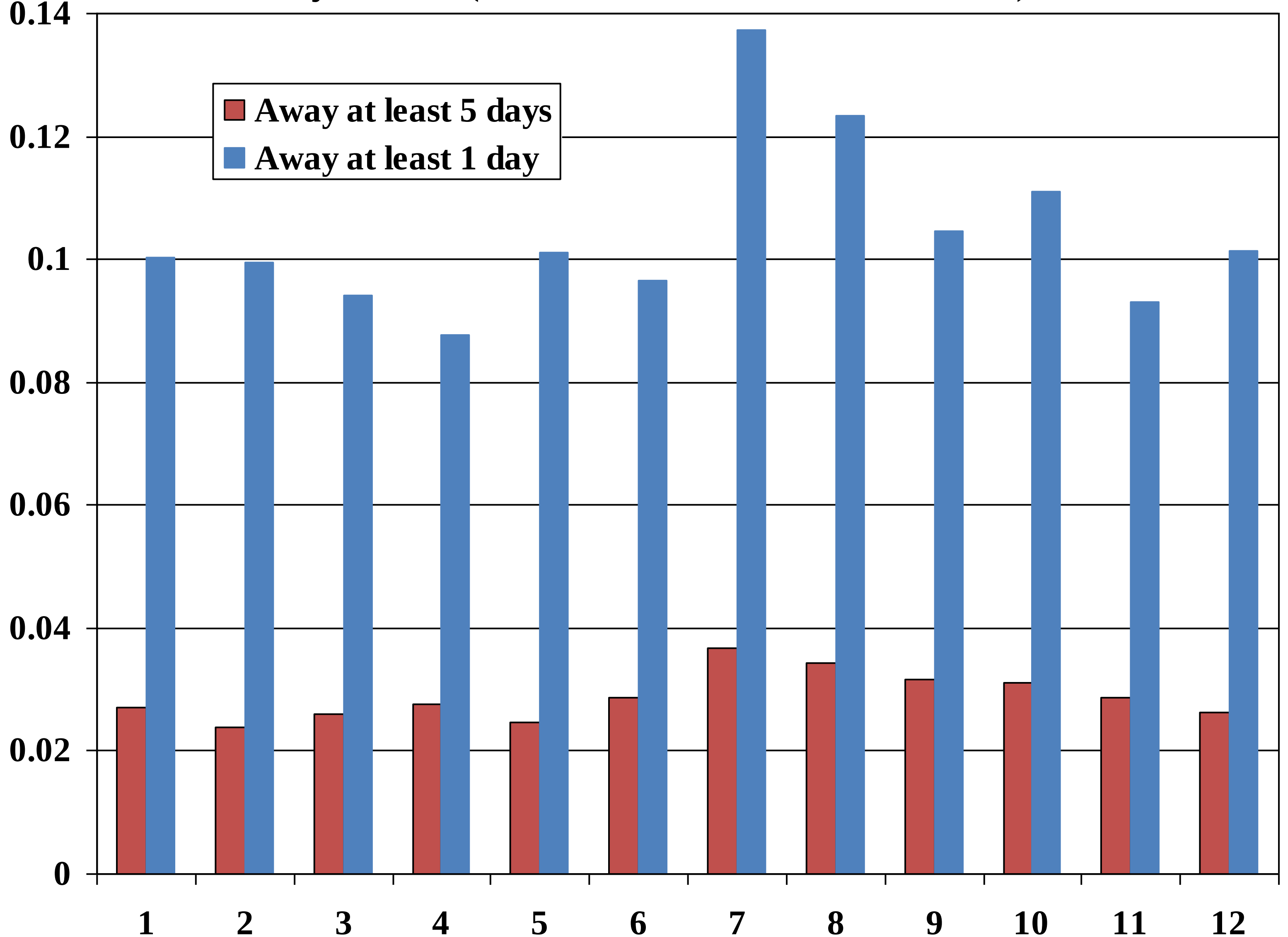


Figure 4. Proportion of Workers Among Men Aged 19-49 in Urban Areas in July, by Year (Source: ICRISAT VLS 2010-2014)

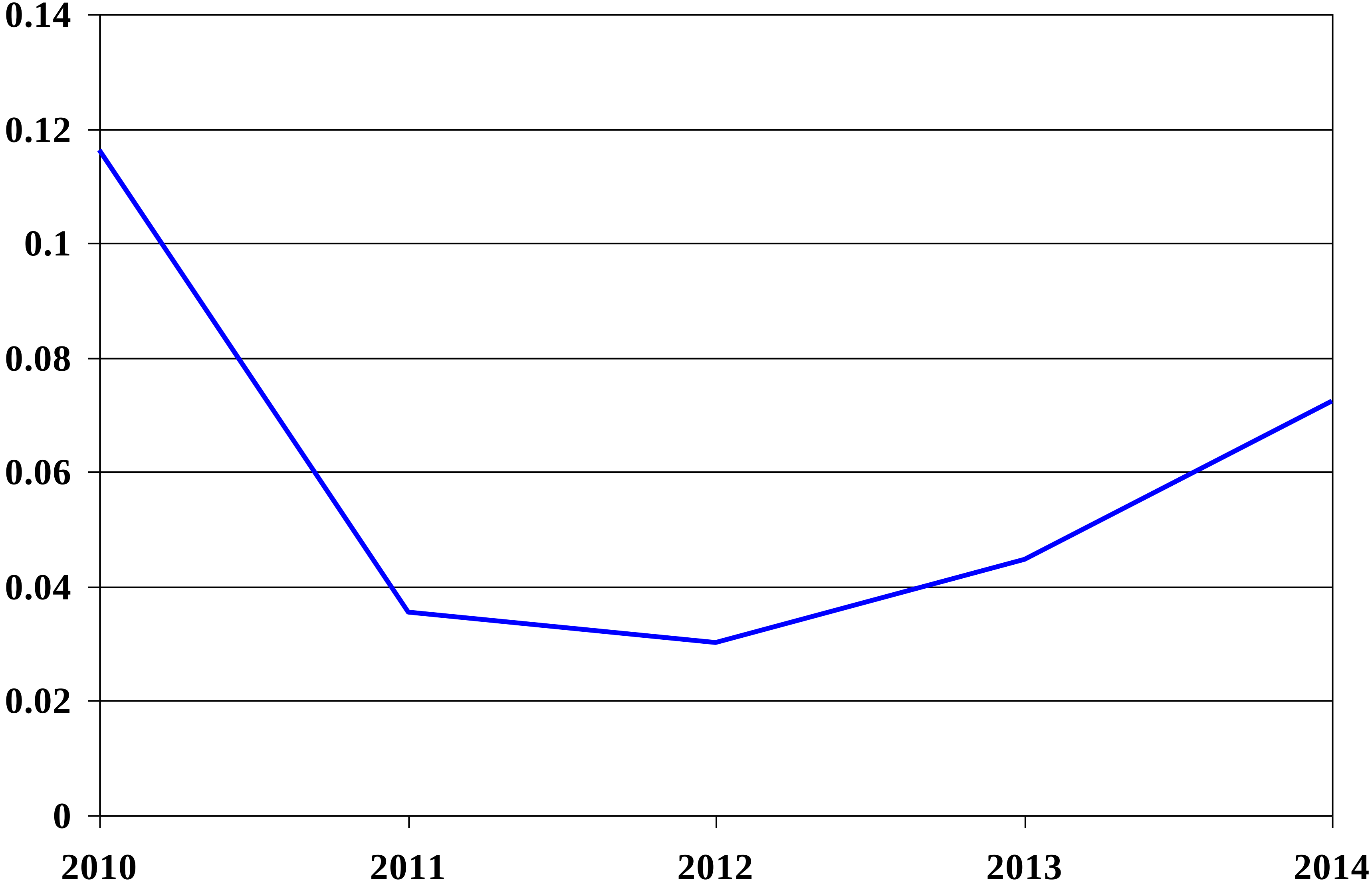


Figure 5: Lowess-Smoothed Relationship between Inter-Village Distance (Km) and June-August Rainfall Correlation, Andhra Pradesh and Uttar Pradesh 1999-2007

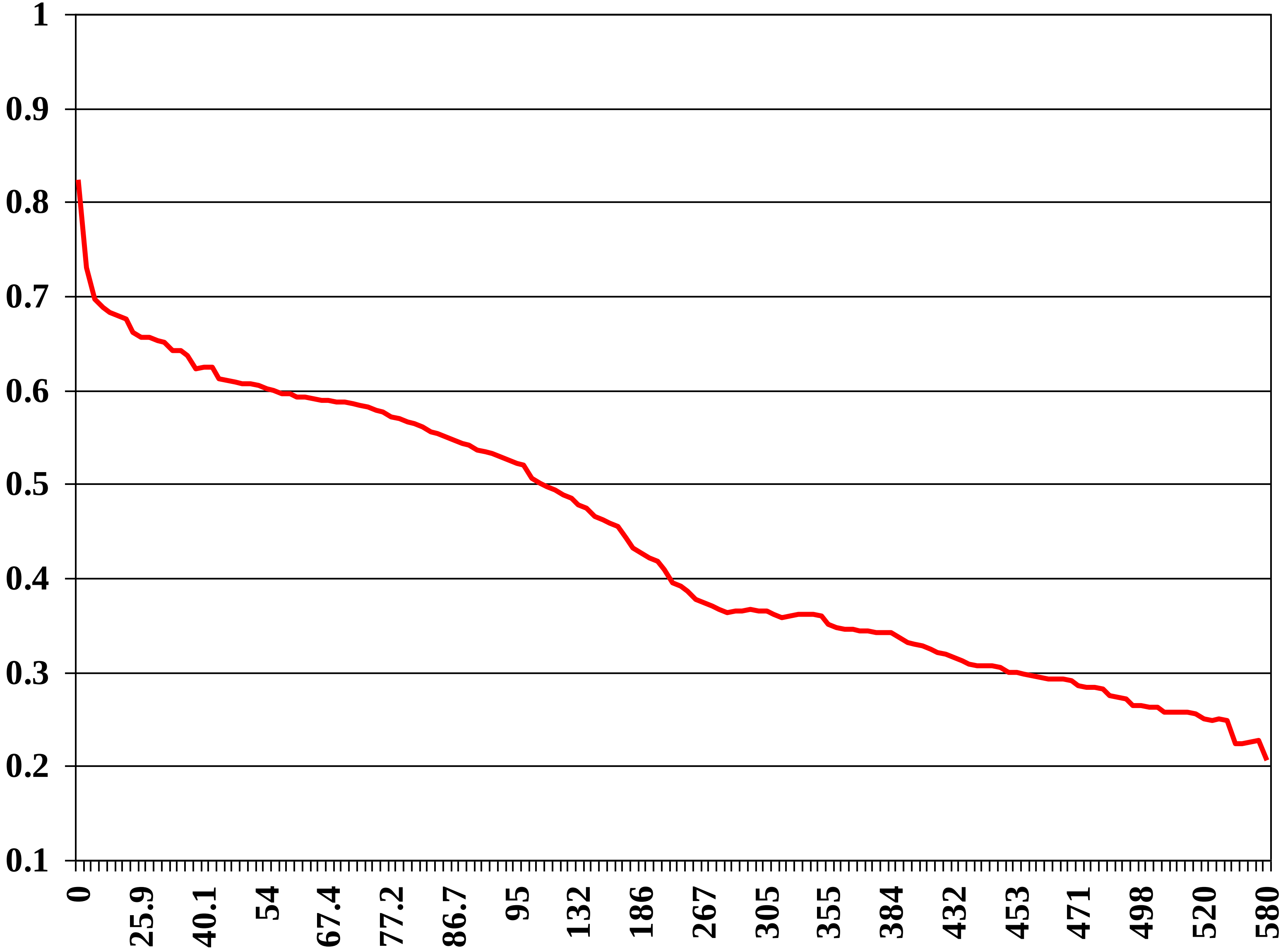


Table 1
IMD Forecasts (Normal=100), by Area and Year, for the ICRISAT Villages, 2009-2014

Year/area	Southern Peninsula: Andhra Pradesh, Karnataka	Central: Gujurat, Maharashtra, Madhya Pradesh
2009	93	99
2010	102	99
2011	94	95
2012	95	96
2013	98	98
2014	93	94

Table 2
Forecast Skill and Rainfall Characteristics, Six Original ICRISAT Villages 2005-2011, by Village

State	Maharashtra				Andhra Pradesh	
Village	Kalman	Kanzara	Kinkheda	Shirapur	Aurepalle	Dokur
Mean July-September rainfall (mm)	415.8	582.5	571.1	360.9	586.4	525.4
CV July-September rainfall	.753	.750	.736	.741	.488	.213
Skill (forecast-rainfall ϱ)	.451	.173	.193	.397	-.401	-.161

Table 3
District Characteristics and Forecast Skill, 1999-2007
REDS Districts

Sample	All Districts		Skill Districts
Variable	Skill District	*q*	*q*
Mean *kharif* rainfall (x 10^{-3})	0.389***	0.141***	0.0215
	(0.166)	(0.0696)	(0.124)
CV *kharif* rainfall (x 10^{-3})	-0.185	-0.0660	-.0913
	(0.425)	(0.232)	(0.366)
Fraction farmers growing rice	0.282***	0.142***	0.143
	(0.104)	(0.0435)	(0.117)
Fraction of villages with a bank < 5 km	0.208***	-0.0760	-0.0311
	(0.0917)	(0.0411)	(0.0838)
Fraction soil red	-0.367***	-0.153**	-0.0982
	(0.165)	(0.0810)	(0.206)
Fraction soil black	-0.311***	-0.111***	-0.0236
	(0.143)	(0.0562)	(0.147)
Fraction soil sandy	-0.266	-0.172**	-0.164
	(0.238)	(0.0939)	(0.223)
Fraction soil clay	-0.292***	-0.142***	-0.0635
	(0.143)	(0.0630)	(0.124)
H_0: All coefficients = 0 F [p]	6.15	5.58	0.78
	[0.0000]	[0.0000]	[0.6253]
N	97	97	39

Robust standard errors in parentheses.

Table 4
Farmer Fixed-Effect Estimates of the Effect of the IMD Forecast on Planted HYV Acreage: ARIS 1969-71

Variable	All Farmers	Farmers Where There are Forecasts
IMD forecast index	1.33***	1.34***
	(0.411)	(0.419)
N	4,784	2,704

Standard errors clustered at the village level in parentheses. Specification contains a linear trend.

Table 5
Farmer Fixed-Effect Estimates of the Effects of the IMD Forecast and Forecast Skill on Log Planting-Stage Investment, REDS 1999-2007

Variable	No additional interactions	Rainfall, rice and bank interactions	Rainfall, rice, bank and soil interactions
IMD forecast	-0.0604	-0.152**	-0.0612
	(0.0397)	(0.0796)	(0.0796)
IMD forecast x *q*	0.166***	0.179**	0.150
	(0.0788)	(0.0951)	(0.109)
H_0: Rainfall, rice and bank interactions = 0, F(4,208) [p]	-	1.31	1.18
		[0.2659]	[0.3187]
H_0: Soil interactions = 0, F(4,208) [p]	-	-	1.09
			[0.3646]
H_0: Rainfall, rice, bank and soil interactions = 0, F(8,208) [p]	-	-	1.45
			[0.1792]
N	4,438	4,438	4,438

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

Table 6
Farmer Fixed-Effect Estimates of the IMD Forecast Effect on *Kharif*-Season Log Planting-Stage Investment ICRISAT Villages, 2009-2014

Variable	(1)	(2)	(3)	(4)
Forecast	0.0245*** (0.00513)	0.0322*** (0.00574)	-	-
Forecast x no skill village	-	-0.0257*** (0.0124)	-	-
Forecast<98	-	-	-0.158*** (0.0251)	-0.181*** (0.0269)
Forecast<98 x no skill village	-	-	-	0.137* (0.0787)
N	3,403	3,403	3,403	3,403

Standard errors in parentheses. All specifications include a linear trend variable.

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) dπ/dRain with good forecast at mean rainfall:	-	36.6***
		(5.68)
(b) dπ/dRain with bad forecast at mean rainfall:	-	28.5***
		(5.51)
(a) - (b)	-	8.04***
		(3.55)
N	2,478	2,478

Table 8
Household Fixed-Effect Estimates of the IMD Forecast and Minimum Wage Effects on *Kharif*-Season Planting-Stage Migration by Rural 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 9
District Fixed-Effect Estimates of the IMD Forecast and Minimum Wage Effects on *Kharif*-Season Planting-Stage Migration by Rural Men Aged 14-49
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.

Table 10
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 11
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.

Table 12
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 13
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.

Appendix

Preliminaries: Demand for Labor and Technology Choice

1. Symmetry

The model with if $F = G$ with $q = q_0$ is indistinguishable from that with $F = B$ and $q_1 = 1 - q_0$. Therefore the equilibrium wage vector $\boldsymbol{w}_G = \boldsymbol{w}_B$ if $q = 0.5$.

2. Choice of Technology is separable

The farmer chooses the level of risk knowing the forecast and wage vector. Consider $F = G$; the argument is entirely symmetrical for $F = B$. The first order conditions with respect to labor demand and technology choice are:

	$\beta x_{1G}^{\beta-1}\left[(1-q)(1-\rho w_{bG})(1-R_G)c_{bG}^{-\gamma} + q(1+R_G)(1-\rho w_{gG})\theta c_{gG}^{-\gamma}\right] - w_{1G}c_{1G}^{-\gamma} = 0$	(22)
	$q\left(1-\rho w_{gG}\right)\theta c_{gG}^{-\gamma} - (1-q)(1-\rho w_{bG})c_{bG}^{-\gamma} \leq 0; R_G \geq 0$	(23)

(22) holding with complementary slackness.

So

	$\frac{c_{bG}}{c_{gG}} \leq \left(\frac{(1-\rho w_{bG})(1-q)}{(1-\rho w_{gG})q\theta}\right)^{\frac{1}{\gamma}}$	(24)

and from the budget constraints we have

	$\frac{c_{bG}}{c_{gG}} = \frac{(1-\rho w_{bG})(1-R_G)}{\left(1-\rho w_{gG}\right)\theta(1+R_G)}$	(25)

(23) and (24) imply

	$R_G = \max\left[0, \frac{1-\left[\left(\frac{1-\rho w_{bG}}{\theta\left(1-\rho w_{gG}\right)}\right)^{\frac{1}{\gamma}-1}\left(\frac{(1-q)}{q}\right)\right]^{\frac{1}{\gamma}}}{1+\left[\left(\frac{1-\rho w_{bG}}{\theta\left(1-\rho w_{gG}\right)}\right)^{\frac{1}{\gamma}-1}\left(\frac{(1-q)}{q}\right)\right]^{\frac{1}{\gamma}}}\right]$	(26)

Parallel calculations provide the analogous result for R_B. For $R_G > 0$ and $\gamma < 1$,

$$\frac{\partial R_G}{\partial q} = \frac{\frac{2}{\gamma} A \left(\frac{1-q}{q}\right)^{\frac{1}{\gamma}-1} \frac{1}{q^2}}{\left(1 + A\left(\frac{(1-q)}{q}\right)^{\frac{1}{\gamma}}\right)^2} > 0$$

with $A = \left(\frac{1-\rho w_{bG}}{\theta(1-\rho w_{gG})}\right)^{\frac{1}{\gamma}-1}$.

3. Labor Demand

From (21) and (22)

$$\beta x_{1G}^{\beta-1}\left[(1-q)(1-\rho w_{bG})(1-R_G)\ \frac{(1-\rho w_{gG})q\theta}{(1-\rho w_{bG})(1-q)} + q(1+R_G)(1-w_{gG})\theta\right] = w_{1G}\left(\frac{c_{1G}}{c_{gG}}\right)^{-\gamma} \tag{27}$$

From the budget constraints we have

$$2\beta x_{1G}^{\beta-1} q(1-\rho w_{gG})\theta = w_{1G}\left(\frac{Y - w_1 x_{1G}}{\theta x_{1G}^{\beta}(1+R_G)(1-\rho w_{gG})}\right)^{-\gamma} \tag{28}$$

Therefore

$$x_{1G}^{\beta-1-\beta\gamma} - \frac{(Y - w_1 x_{1G})^{-\gamma} w_{1G}(1+R_G)^{\gamma}\left(1-\rho w_{gG}\right)^{\gamma-1}\theta^{\gamma-1}}{2\beta q} = 0 \tag{29}$$

implicitly defines x. Define the LHS of (28) as G_x. Noting that

$$\begin{aligned}\frac{\partial G_x}{\partial x} &= (\beta-1-\beta\gamma)x_{1G}^{\beta-2-\beta\gamma} - \frac{\gamma w_1 c_{1G}^{-\gamma-1} w_{1G}(1+R_G)^{\gamma}\left(1-\rho w_{gG}\right)^{\gamma-1}\theta^{\gamma-1}}{2\beta q} < 0\\ \frac{\partial G_x}{\partial w_{1G}} &= \frac{-(1+R_G)^{\gamma}\left(1-\rho w_{gG}\right)^{\gamma-1}\theta^{\gamma-1}(\gamma c_{1G}^{-\gamma-1} x_{1G} w_{1G} + c_{1G}^{-\gamma})}{2\beta q} < 0\end{aligned} \tag{30}$$

We have

Implication A:

$$\frac{dx_{1G}}{dw_{1G}} < 0.$$

Similarly

$$\frac{\partial G_x}{\partial w_{gG}} = (\gamma-1)\rho\frac{(Y - w_1 x_{1G})^{-\gamma} w_{1G}(1+R_G)^{\gamma}\left(1-\rho w_{gG}\right)^{\gamma-2}\theta^{\gamma-1}}{2\beta q} < 0 \tag{31}$$

for $\gamma < 1$, and we can show

$$\frac{dx_{1G}}{dw_{1G}} < \frac{dx_{1G}}{dw_{gG}} < 0.$$

Planting stage labor demand after a forecast of G is increasing in the skill of the forecast.

	$$\frac{\partial G_x}{\partial q} = \frac{(Y - w_1 x_{1G})^{-\gamma} w_{1G} \left(1 - \rho w_{gG}\right)^{\gamma-1} \theta^{\gamma-1}}{2\beta q^2} \Big[(1 + R_G)^{\gamma} - q\gamma(1 + R_G)^{\gamma-1} \frac{\partial R_G}{\partial q}\Big]$$	(32)

For $\gamma < 1, \frac{\partial G_x}{\partial q} > 0$, so

$$\frac{dx_{1G}}{dq} > 0.$$

4. Migration and wages

There will be a cutoff planting stage reservation wage w_{uF}^* such that a worker migrates for the planting stage if and only if he draws an urban wage for the planting stage greater than that reservation wage $(w_{1u} \geq w_{uF}^*)$.

w_{uF}^* is defined as the urban wage offer that equalizes a worker's expected utility from migrating in the planting stage with the expected utility from working in the village in the planting stage given a forecast of F.

Consider F=G. w_{uG}^* is defined by

	$$\begin{aligned} W: v(w_{uG}^*) + q\big[w_{gG} f_2 v\big(w_{gG}\big) + \big(1 - w_{gG} f_2\big) E\big(v(w_u)\big\vert w_u > w_{gG}\big)\big] \\ + (1-q)[w_{bG} f_2 v(w_{bG}) + (1 - w_{bG} f_2) E_2(v(w_u) \vert w_u > w_{bG})] \\ - \{v(w_{1G}) \\ + q\big[w_{gG} f_1 v\big(w_{gG}\big) + \big(1 - w_{gG} f_1\big) E_1\big(v(w_u)\big\vert w_u > w_{gG}\big)\big] \\ + (1-q)[w_{bG} f_1 v(w_{bG}) + (1 - w_{bG} f_1) E_1(v(w_u) \vert w_u > w_{bG})]\} \\ = 0 \end{aligned}$$	(33)

The LHS of (32), which we denote as W, is monotonically increasing in w_{ug}^*, so a simple application of the IFT shows that (32) defines the trigger urban wage as a function of the rural wage vector $\boldsymbol{w}_G$: $w_{uG}^*\big(w_{1G}, w_{gG}, w_{bG}\big)$. It is immediately apparent that $\frac{dw_{uG}^*}{dw_{1G}} > 0$. The effects of the harvest stage wages on the trigger urban wage are positive as well. $\frac{dw_{uG}^*}{dw_{gG}} > 0$ if $\frac{\partial W}{\partial w_{gG}} > 0$. Differentiating (32):

$$
\begin{aligned}
\frac{dW}{dw_{gG}} = q\Bigg[&(f_2 - f_1)v(w_{gG}) + w_{gG}(f_2 - f_1)v'(w_{gG}) - f_2E_2\big(v(w_u)\big|w_u > w_{gG}\big) \\
&+ (1 - w_{gG}f_2)\frac{dE_2\big(v(w_u)\big|w_u > w_{gG}\big)}{dw_{gG}} + f_1E_1\big(v(w_u)\big|w_u > w_{gG}\big) \\
&- (1 - w_{gG}f_1)\frac{dE_1\big(v(w_u)\big|w_u > w_{gG}\big)}{dw_{gG}}\Bigg] \\
= q\Bigg[&(f_2 - f_1)v(w_{gG}) + w_{gG}(f_2 - f_1)v'(w_{gG}) - f_2E_2\big(v(w_u)\big|w_u > w_{gG}\big) \\
&+ (1 - w_{gG}f_2)\frac{f_2}{1 - w_{gG}f_2}E_2\big(v(w_u)\big|w_u > w_{gG}\big) + f_1E_1\big(v(w_u)\big|w_u > w_{gG}\big) \\
&- (1 - w_{gG}f_1)\frac{f_1}{1 - w_{gG}f_1}E_1\big(v(w_u)\big|w_u > w_{gG}\big)\Bigg] \\
= q\big[&(f_2 - f_1)v(w_{gG}) + w_{gG}(f_2 - f_1)v'(w_{gG}) - f_2E_2\big(v(w_u)\big|w_u > w_{gG}\big) \\
&+ f_2E_2\big(v(w_u)\big|w_u > w_{gG}\big) + f_1E_1\big(v(w_u)\big|w_u > w_{gG}\big) - f_1E_1\big(v(w_u)\big|w_u > w_{gG}\big)\big] \\
= q\big[&(f_2 - f_1)v(w_{gG}) + w_{gG}(f_2 - f_1)v'(w_{gG})\big] < 0
\end{aligned}
$$

Therefore, $\frac{dw_{uG}^*}{dw_{gG}} > 0$. A parallel calculation shows $\frac{dw_{uG}^*}{dw_{bG}} > 0$, and three similar calculations show $\frac{dw_{uB}^*}{dw_{1B}}, \frac{dw_{uB}^*}{dw_{gB}}, \frac{dw_{uB}^*}{dw_{bB}} > 0$.

The trigger urban wage offer is less than the growing stage rural wage:

$$
\begin{aligned}
&v(w_{1G}) - v(w_{uG}^*) \\
&\quad < q\Big[w_{gG}f_2v(w_{gG}) + (1 - w_{gG}f_2)E_1\big(v(w_u)\big|w_u > w_{gG}\big) \\
&\quad - \Big(w_{gG}f_2v(w_{gG}) + (1 - w_{gG}f_2)E_2\big(v(w_u)\big|w_u > w_{gG}\big)\Big)\Big] \\
&\quad + (1 - q)\big[w_{bG}f_2v(w_{bG}) + (1 - w_{bG}f_2)E_1(v(w_u)|w_u > w_{bG}) \\
&\quad - \big(w_{bG}f_2v(w_{bG}) + (1 - w_{bG}f_2)E_2(v(w_u)|w_u > w_{bG})\big)\big] \\
&\quad < q\Big[w_{gG}f_2v(w_{gG}) + (1 - w_{gG}f_2)E_2\big(v(w_u)\big|w_u > w_{gG}\big) \\
&\quad - \Big(w_{gG}f_2v(w_{gG}) + (1 - w_{gG}f_2)E_2\big(v(w_u)\big|w_u > w_{gG}\big)\Big)\Big] \\
&\quad + (1 - q)\big[w_{bG}f_2v(w_{bG}) + (1 - w_{bG}f_2)E_2(v(w_u)|w_u > w_{bG}) \\
&\quad - \big(w_{bG}f_2v(w_{bG}) + (1 - w_{bG}f_2)E_2(v(w_u)|w_u > w_{bG})\big)\big] = 0
\end{aligned}
\tag{34}
$$

The first inequality is a consequence of $f_1 > f_2$, along with $E(v(w_u)|w_u > w) > v(w)$. The second inequality is a consequence of $E_2(v(w_u)|w_u > w) > E_1(v(w_u)|W_u > w)$. Analogous reasoning holds for $F = B$.

Therefore,

Implication B: migration in the planting stage $M_{1F} = \big(1 - w_{uF}^*(w_{1F}, w_{gF}, w_{bF}, F)f_1\big)$, *with* $\frac{dM_{1F}}{dw_{1F}}, \frac{dM_F}{dw_{sF}} < 0$.

Migration in state s of the harvest stage is $M_{sF} = 1 - (S_1f_1 + (1 - S_1)f_2)w_{sF}$. The supply of labor in stage 1 is $S_1 = w_{uF}^*\big(w_{1F}, w_{gF}, w_{bF}, F\big)f_1$. In the harvest stage, the supply of labor is

$S_{sF} = (S_1 f_1 + (1 - S_1) f_2) w_{sF}$	(35)

5. Harvest Stage Equilibrium in the Rural Labor Market

For either forecast, labor demand in the bad state of the harvest stage is less than labor demand in the good state:

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

Equilibrium requires that harvest stage labor supply in the good state be larger than harvest stage labor supply in the bad state $\left(S_{gF} > S_{bF}\right)$. Therefore,

Implication C: $w_{gF} = \frac{S_{gF}}{(S_1 f_1 + (1 - S_1) f_2)} > \frac{S_{bF}}{(S_1 f_1 + (1 - S_1) f_2)} = w_{bF}$.

Specifically,

$$\frac{w_{gF}}{w_{bF}} = \frac{\frac{\rho x_{1F}^{\beta}\theta(1 + R_F)}{(S_1 f_1 + (1 - S_1) f_2)}}{\frac{\rho x_{1F}^{\beta}(1 - R_F)}{(S_1 f_1 + (1 - S_1) f_2)}} = \frac{\theta(1 + R_F)}{(1 - R_F)}$$	(36)

In addition,

Implication D: $S_{gF} > S_{bF}$ *requires that harvest stage migration is less in the good state than in the bad state of the harvest period (*$M_{gF} < M_{bF}$*).*

Distinguishing the Degree of Risk Aversion

In the absence of a safe asset or credit market, the choice of planting stage labor is the primary tool for moving resources across stages, while the choice of the riskiness of the technology is the first order tool for calibrating risk across harvest stage states of nature. If the technology is such that harvest season profits are always (weakly) higher in the good state, then choosing $R_F > 0$ implies that risk aversion cannot be too strong. Define profit in state s of the harvest stage as $Q_{sF}(1 - w_{sF}) = \pi_{sF}$.

Proposition 1: *If* $\pi_{gF} \geq \pi_{bF}$ *at* $R_G = 0$ *and* $R_G > R_B$ *for* $q \in [0.5,1]$ *then* $\gamma < 1$.

Proof: $\pi_{gF} > \pi_{bF}$ implies $\frac{(1-R_G)}{(1+R_G)} = 1 < \frac{\theta(1-\rho w_{gG})}{1-\rho w_{bG}}$

And $R_G > R_B$ implies

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

At $q = \frac{1}{2}$,

$$\left(\frac{(1 - \rho w_{gG})\theta}{(1 - \rho w_{bG})}\right)^{1-\frac{1}{\gamma}} < 1 < \frac{\theta(1 - \rho w_{gG})}{1 - \rho w_{bG}}.$$

Therefore, $\gamma < 1$. ■

Equilibrium with $\gamma < 1$

We can reduce the problem of solving for the equilibrium wage vector to two dimensions when $\gamma < 1$ by noting that harvest season relative wages (from (35) and (25)) are:

$$\left(\frac{w_{gF}}{w_{bF}}\right)^{\gamma}\left(\frac{1-\rho w_{gF}}{1-\rho w_{bF}}\right)^{1-\gamma} = \theta\left(\frac{q}{(1-q)}\right)^{J_F} \tag{37}$$

for $J_G = 1$ and $J_B = -1$. (16) implicitly defines w_{bF} as a function of w_{gF}. To calculate an equilibrium:

1. For every w_{gF}, calculate the consistent w_{bF} from harvest season relative wage equilibrium (16). Note that for $\gamma \leq 1$, $w_{bF}(w_{gF})$ is monotonic and $1 > \frac{dw_{bF}}{dw_{gF}} > 0$.
2. So the problem is to find $\boldsymbol{\omega_F} = (w_{1F}, w_{gF})'$ such that $\boldsymbol{w}_F = \left(w_{1F}, w_{gF}, w_{bF}(w_{gF})\right)'$ solves the 2 equations:

$$\begin{aligned} S_{1F}(\boldsymbol{wS}_F) - x_F(\boldsymbol{w}_F) &= \boldsymbol{0} \\ w_{gF}(S_{1F}(\boldsymbol{w}_F)f_1 + (1 - S_{1F}(\boldsymbol{w}_F))f_2) - \rho\,\theta\left(1 + R_F(\boldsymbol{w}_F)\right)\left(x_F(\boldsymbol{w}_F)\right)^{\beta} &= 0 \end{aligned} \tag{38}$$

We have already established that $\frac{dS_{1F}}{dw_{1F}} > 0$ and $\frac{dS_{1F}}{dw_{gG}} = \frac{\partial S_{1F}}{\partial w_{gG}} + \frac{\partial S_{1F}}{\partial w_{bG}}\frac{dw_{bG}}{dw_{gG}} > 0$. We have established

$$\frac{dS_{1F}}{dw_{1F}} > \frac{dS_{1F}}{dw_{gF}} > 0, \frac{dx_F}{dw_{1F}} < \frac{dx_F}{dw_{gF}} < 0 \tag{39}$$

Define

$$S_{gF}(w_{1F}, w_{gG}; q\,) = w_{gF}(S_{1F}(\boldsymbol{w}_F)f_1 + (1 - S_{1F}(\boldsymbol{w}_F))f_2)$$

So

$$\frac{dS_{gF}}{dw_{1F}} = w_{gF}\left(\frac{dS_{1F}}{dw_{1F}}f_1 - \frac{dS_{1F}}{dw_{1F}}f_2\right) = w_{gF}\frac{dS_{1F}}{dw_{1F}}(f_1 - f_2) > 0$$

And

$$\frac{dS_{gF}}{dw_{gF}} = w_{gF}\frac{dS_{1F}}{dw_{gF}}(f_1 - f_2) + (S_{1F}(\boldsymbol{w}_F)f_1 + (1 - S_{1F}(\boldsymbol{w}_F))f_2) > 0.$$

A similar calculation shows $\frac{dS_{gG}}{dq} > 0$.

Define $D_{gF}(w_{1F}, w_{gG}; q) = \rho\theta\left(1 + R_F(\boldsymbol{w}_F)\right)(x_F(\boldsymbol{w}_F))^{\beta}$ so

$$\frac{dD_{gF}}{dw_{1F}} = \rho\beta\theta\left(1 + R_F(\boldsymbol{w}_F)\right)(x_F(\boldsymbol{w}_F))^{\beta-1}\frac{dx_F}{dw_{1F}} < 0$$

$$\frac{dD_{gF}}{dw_{gG}} = \rho\beta\theta\left(1 + R_F(\boldsymbol{w}_F)\right)(x_F(\boldsymbol{w}_F))^{\beta-1}\frac{dx_F}{dw_{gG}} + \rho\theta R_F(\boldsymbol{w}_F)(x_F(\boldsymbol{w}_F))^{\beta}\frac{dR_F}{dw_{gG}} < 0$$

Therefore

	$\frac{dS_{gF}}{dw_{gF}} > \frac{dS_{gF}}{dw_{1F}} > 0, \frac{dD_{gF}}{dw_{gF}} < \frac{dD_{gF}}{dw_{1F}} < 0$	(40)

Testable Implications of the Model when $\gamma < 1$

Implication 1: Planting state labor demand is higher after a forecast of good rain than after a forecast of poor rain: $x_{1G} \geq x_{1B}$.

By the symmetry of the model, we know that at $q = 0.5$, $x_{1G} = x_{1B}$, and that $\frac{dx_{1G}}{dq} = -\frac{dx_{1B}}{dq}$. Therefore, $\frac{dx_{1G}}{dq} > 0 \Rightarrow x_{1G} > x_{1B}$. Let $\boldsymbol{J}$ be the (2×2) Jacobian matrix of (37), so that

$$\begin{bmatrix} \frac{dw_{1G}}{dq} \\ \frac{dw_{gG}}{dq} \end{bmatrix} = -[\boldsymbol{J}]^{-1} \begin{bmatrix} \frac{\partial S_{1G}}{dq} - \frac{\partial x_{1G}}{dq} \\ \frac{dS_{gG}}{dq} - \frac{dD_{gG}}{dq} \end{bmatrix}$$

and

$$\frac{dx_{1G}}{dq} = \frac{\partial x_{1G}}{\partial w_{1G}} \frac{dw_{1G}}{dq} + \frac{\partial x_{1G}}{\partial w_{gG}} \frac{dw_{gG}}{dq} + \frac{\partial x_{1G}}{\partial q}$$

We established above that the direct effect $\frac{\partial x_{1G}}{\partial q} > 0$. The conditions on the derivatives in (38) and (39) ensure that $\boldsymbol{J}$ is non-singular and that $\frac{dx_{1G}}{dq} > 0$. The algebra is tedious; but the intuition should be clear from Appendix figure A1.

Implication 2: Planting season migration must be less upon a forecast of good weather than upon a forecast of bad weather: $M_{1G} < M_{1B}$.

Planting stage labor market equilibrium requires

$$(1 - M_{1G}) = S_{1G} = x_{1G} > x_{1B} = S_{1B} = (1 - M_{1B}).$$

Implication 3: The difference in migration in the good state of the harvest stage and in the bad state of the harvest stage must be greater after a forecast of good weather: $M_{bG} - M_{gG} > M_{bB} - M_{gB}$.

$R_G \geq R_B$ implies $\frac{Q_{gG}}{Q_{bG}} \geq \frac{Q_{gB}}{Q_{bB}}$. $R_G \geq R_B$ and $x_{1G} > x_{1B}$ together imply $Q_{gG} - Q_{bG} > Q_{gB} - Q_{bB}$. Hence the change in harvest labor demand is higher and migration fall more after a forecast of good than of bad.

Implication 4: There is a greater difference between harvest season wages with good and bad weather realizations after a forecast of good weather than after a forecast of bad weather: $\frac{w_{gG}}{w_{bG}} > \frac{w_{gB}}{w_{bB}}$.

$R_G > R_B$ implies from (34)

$$\frac{w_{gG}}{w_{bG}} = \frac{\theta(1+R_G)}{(1-R_G)} > \frac{\theta(1+R_B)}{(1-R_B)} = \frac{w_{gB}}{w_{bB}}.$$

Implication 5: the wage in the good state of the harvest stage after a forecast of good weather is greater than the wage in the good state of the harvest stage after a forecast of bad weather: $w_{gG} > w_{gB}$.

$x_{1G} > x_{1B}$ and $R_{1G} > R_{1B}$ imply for the harvest stage labor markets to clear that

$$\begin{aligned} w_{gG}(x_{1G}f_1 + (1-x_{1G})f_2) &= \rho x_{1G}^{\beta}\theta(1+R_{1G}) > \rho x_{1B}^{\beta}\theta(1+R_{1B}) \\ &= w_{gB}(x_{1B}f_1 + (1-x_{1B})f_2) > w_{gB}(x_{1G}f_1 + (1-x_{1G})f_2) \end{aligned}$$

because $f_2 < f_1$. Therefore, $w_{gG} > w_{gB}$.

Wage Floors

A statutory wage floor at a fixed level w_m generated by an employment guarantee scheme implies that an equilibrium must have $(w_{1F}, w_{gF}, w_{bF}) \equiv \boldsymbol{w_F}$ such that $\boldsymbol{w_F} \geq w_m$, with labor market clearing conditions defined in text equation (16). We consider the effect of a change in the level of the statutory wage floor on equilibrium rural wages.

We now show

Proposition 2: Suppose that the equilibrium wage vector is $(w_{1F}^*, w_{gF}^*, w_{bF}^*) \equiv \boldsymbol{w_F^*}$ such that $\boldsymbol{w_F^*} \geq w_m$, and $\boldsymbol{w_F^*} \neq w_m$. *Then if a small increase in the statutory minimum wage* w_m *changes the equilibrium wage vector, it must reduce the equilibrium wage in at least one state of one stage of production.*

Proof: The proposition rules out the trivial case in which $\boldsymbol{w_F^*} = w_m$: given forecast F, the wage floor is binding in each state of each stage of production. Rural labor demand is less than rural labor supply in each state and stage, and the excess supply is employed in the employment guarantee scheme. An increase in w_m obviously increases all rural wages.

Similarly, the proposition rules out the trivial case of $\boldsymbol{w_F^*} \gg w_m$, where the wage floor is never binding.

We need not consider any case in which $w_{gF}^* = w_m < w_{bF}^*$ because the good state harvest stage labor market equilibrium requires

$$w_{gF}^*(S_{1F}(\boldsymbol{w_F^*})f_1 + (1 - S_{1F}(\boldsymbol{w_F^*}))f_2) \geq \rho\theta\big(1 + R_F(\boldsymbol{w_F^*})\big)\big(x_F(\boldsymbol{w_F^*})\big)^{\beta},$$

but the bad state harvest stage labor market equilibrium is

$$w_{bF}^*(S_{1F}(\boldsymbol{w_F^*})f_1 + (1 - S_{1F}(\boldsymbol{w_F^*}))f_2) = \rho\big(1 - R_F(\boldsymbol{w_F^*})\big)\big(x_F(\boldsymbol{w_F^*})\big)^{\beta},$$

which requires $w_{gF}^* \geq w_{bF}^*$.

Therefore, for any forecast F, there are 2 cases to consider:

A. The planting stage rural labor equilibrium holds with equality: $EQ_{1F}(\boldsymbol{w}_F^*) = S_{1F}(\boldsymbol{w}_F^*) - x_F(\boldsymbol{w}_F^*) = 0$. We have shown that $S_{1F}(\boldsymbol{w}_F)$ is monotonically increasing in each of its three wage arguments, and that $x_F(\boldsymbol{w}_F)$ is monotonically decreasing in each of its arguments. Therefore, $EQ_{1F}(\boldsymbol{w}_F)$ is monotonically decreasing in each wage. Therefore at least one wage must decline if w_m increases.
B. The planting stage rural labor equilibrium does not hold with equality $(w_{gF} = w_m)$but the rural labor market equilibrium in the good state does hold with equality:

	$w_{gF}^*(S_{1F}(\boldsymbol{w}_F^*)f_1 + (1 - S_{1F}(\boldsymbol{w}_F^*))f_2) = \rho\theta\big(1 + R_F(\boldsymbol{w}_F^*)\big)\big(x_F(\boldsymbol{w}_F^*)\big)^{\beta}$	(41)

There are two subcases to consider. Either the rural labor market equilibrium in the bad state does or does not hold with equality.

i. If the rural labor market equilibrium in the bad state of the harvest stage holds with equality, then (16) can be used to define $w_{bF}^*(w_{gF})$ with $\frac{dw_{bF}^*}{dw_{gF}} > 0$. The implicit function theorem yields

$$\begin{aligned}\frac{dw_{gF}}{dw_m} = &-\left[w_{gF}\left(\left(\frac{\partial M_{1F}}{\partial w_m}\right)(f_2 - f_1)\right) - \rho\beta\theta(1 + R_F)\frac{\partial x_1}{\partial w_m}x_1^{\beta-1}\right] \\ &\times\left[\big((1 - M_{1F})f_1 + (M_{1F})f_2\big) + w_{gF}\left(\frac{\partial M_{1F}}{\partial w_{gF}} + \frac{\partial M_{1F}}{\partial w_{bF}}\frac{dw_{bF}}{dw_{gF}}\right)(f_2 - f_1)\right. \\ &\left. - \rho\beta\theta(1 + R_F)\left(\frac{\partial x_1}{\partial w_{gF}} + \frac{\partial x_1}{\partial w_{bF}}\frac{dw_{bF}}{dw_{gF}}\right)x_1^{\beta-1}\right]^{-1} < 0.\end{aligned}$$

x_{1F} and M_{1F} are declining in each of their three arguments. $f_2 < f_1$, so the supply of labor in the village increases with both w_m and with w_{gF}. Labor demand in the village declines with both wages. Hence harvest stage wages in both the good and bad weather states are lower in the presence of higher binding wage floors in the planting stage.

ii. The rural labor market equilibrium in the bad state of the harvest stage does not hold with equality ($w_{bF} = w_{1F} = w_m$). (20) then defines $w_{gF}^*(w_m)$, with the planting stage wage and the wage in the bad state of the harvest period both equal to w_m. $f_2 < f_1$, so the LHS of (20) is monotonically increasing in w_{gF} and w_m. The RHS of (20) is monotonically declining in w_{gF} and w_m, so $\frac{dw_{gF}^*(w_m)}{dw_m} < 0$. ■

We show that there exist parameters such that $w_{1F} - w_{1F}^* + \big(prob(s = g|F)\big)(w_{gF} - w_{gF}^*) + \big(1 - prob(s = b|F)\big)(w_{bF} - w_{bF}^*) < 0$ by constructing an example. We compare expected wages when the wage floor in the bad state of the harvest period after a forecast of good rainfall is 5% higher than what would have been the equilibrium without a binding floor to expected wages without the wage floor. The expected wage is lower when there is a binding wage floor when $Y_c = Y_l = 2, \gamma = 0.5, q = 0.51, \beta = 0.5, \rho = 0.55, \theta = 1.55, f_1 = 1.4, f_2 = 0.3$. At these parameter values, the equilibrium wages without a binding wage floor are $(w_{1G}, w_{gG}, w_{bG}) = (0.87, 1.26, 0.16)$ and when the wage floor is binding in the bad state the equilibrium wages are $(w_{1G}^*, w_{gG}^*, w_{bG}^* = w_m) = (0.82, 1.32, 0.17)$.The fall in the planting stage wage is sufficiently large that the expected value of wage earning for landless laborers for landless laborers falls.

Expected Wage Gains from Correct Forecasts

Individuals' migration decisions in planting depend on the forecast if and only if their draw of an urban wage during planting falls into the range $w_G^* > w_u > w_b^*$. So all of the direct benefits of having a correct forecast accrue to the set of people who migrate if the forecast is for bad, and not if the forecast is for good, that is, for the fraction $M_{1B} - M_{1G}$. Suppose the weather turned out well. If the forecast (correctly) been for good, a worker earns

$$w_{1G} + \left(f_1 w_{gG} w_{gG} + \frac{\left(1 - w_{gG} f_1\right)\left(w_{gG} + \frac{1}{f_1}\right)}{2} \right) \tag{42}$$

Had the forecast (incorrectly) been for bad, earnings would be

$$w_u + \left(f_2 w_{gB} w_{gB} + \frac{\left(1 - w_{gB} f_2\right)\left(w_{gB} + \frac{1}{f_2}\right)}{2} \right) \tag{43}$$

Since bad and good outcomes are equally likely, we can add them up and divide by 2 for the effect. We consider here the direct effects of the forecast on migration and their consequences for earnings, so we let $w_{bG} = w_{bB} = w_b < w_g = w_{gG} = w_{gB}$. The difference in expected returns for correct forecasts from incorrect forecasts is

$$\begin{aligned}
&\frac{1}{2}\Bigg[w_u + \left(f_2 w_b w_b + \frac{(1 - w_b f_2)\left(w_b + \frac{1}{f_2}\right)}{2} \right) + w_{1G} \\
&\qquad + \left(f_1 w_g w_g + \frac{\left(1 - w_g f_1\right)\left(w_g + \frac{1}{f_1}\right)}{2} \right) - w_{1G} \\
&\qquad - \left(f_1 w_b w_b + \frac{(1 - w_b f_1)\left(w_b + \frac{1}{f_1}\right)}{2} \right) - w_u \\
&\qquad - \left(f_2 w_g w_g + \frac{\left(1 - w_g f_2\right)\left(w_g + \frac{1}{f_2}\right)}{2} \right) \Bigg] \\
&\qquad = \frac{1}{4}\Big(\left(M_{gB} - M_{gG}\right) w_g - \left(M_{bB} - M_{bG}\right) w_b \Big)
\end{aligned} \tag{44}$$

Appendix Map A1

India Meteorological Department

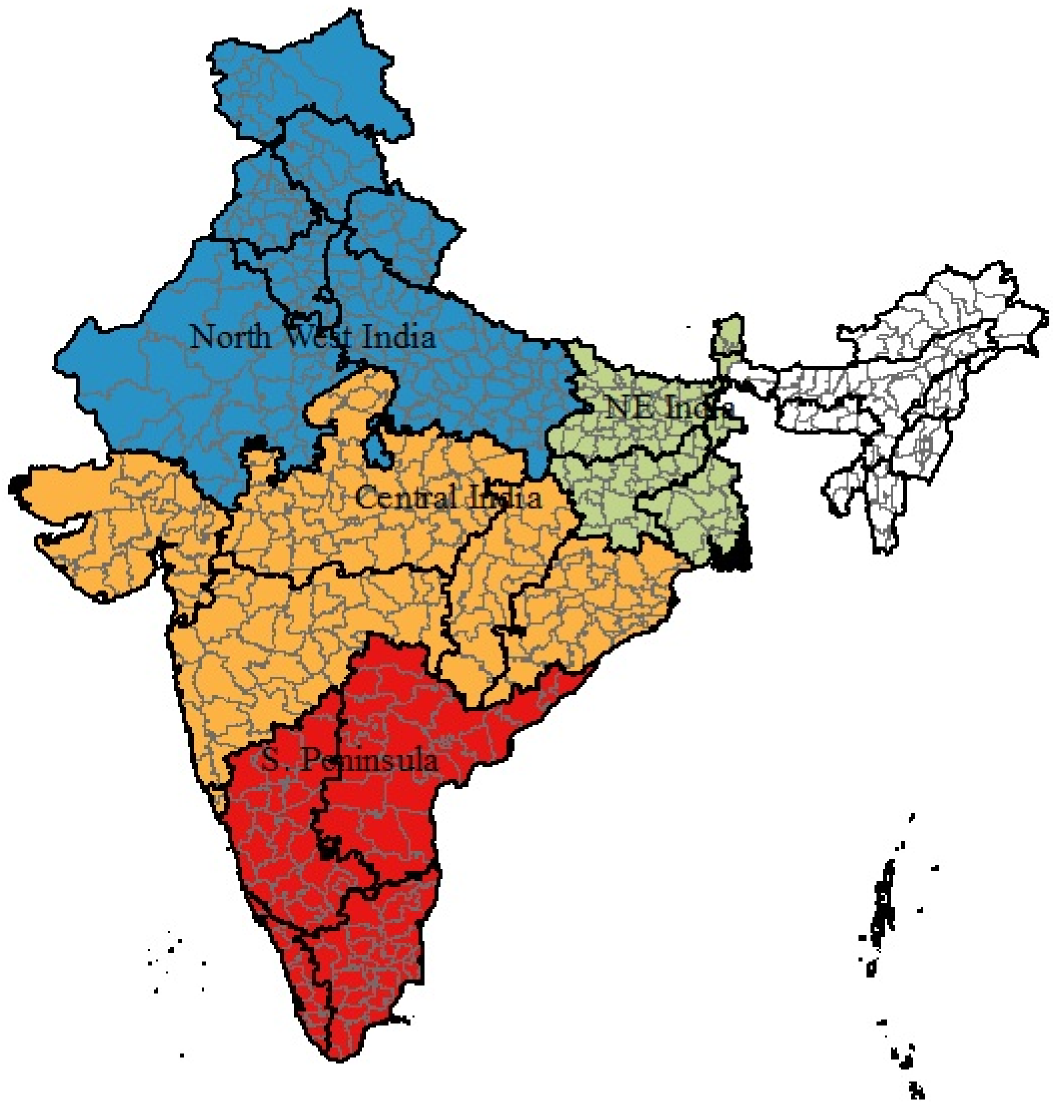
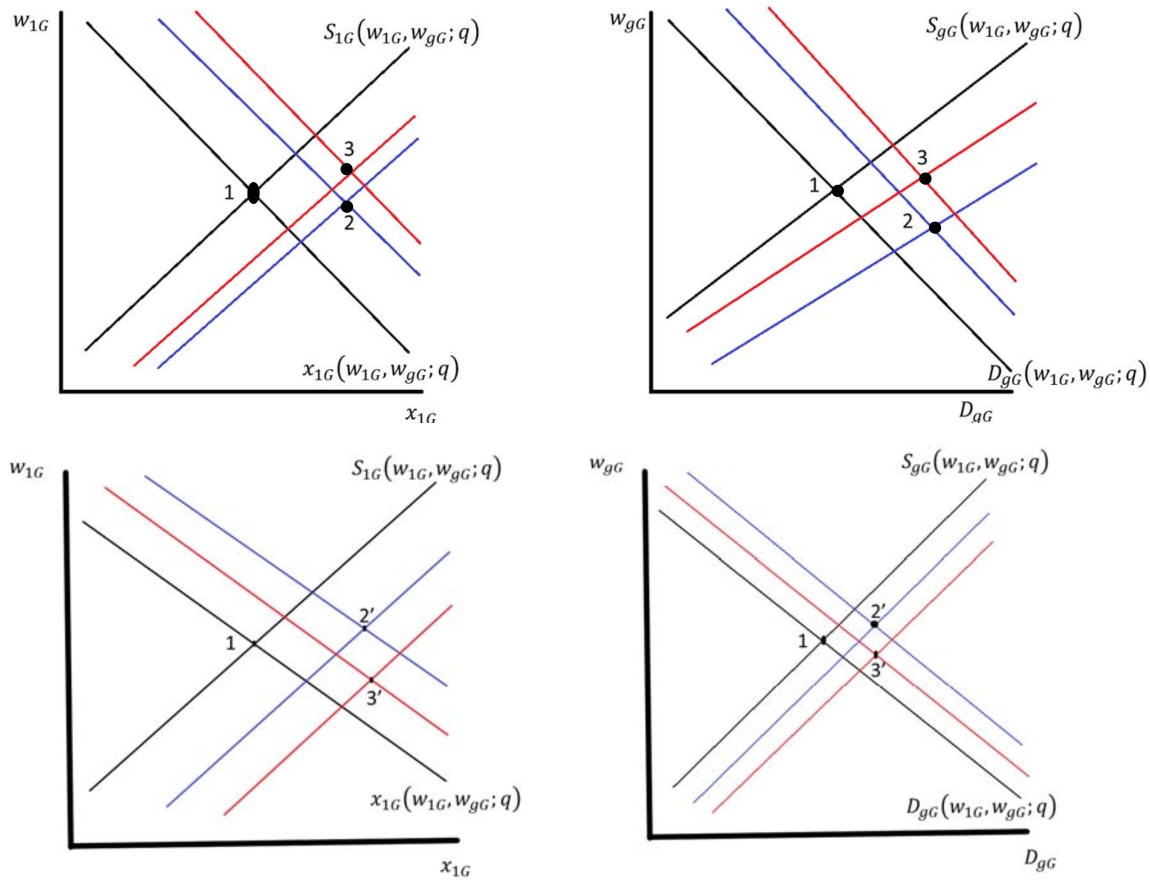


Figure A1: Effect of increase in skill



Planting Season　　　　Harvest Season

Notes: Starting from initial equilibrium wage vector (w_{1G}, w_{gG}) at points (1), an increase in skill has the direct effect of shifting out S_{1G}, x_{1G}, S_{gG} and D_{gG}, increasing demand for labor (in both seasons) to (2). The lower harvest season wage at (2) implies a lower supply of labor in the planting season (and a higher demand for labor in the planting season), making the final equilibrium at point (3). Different parameter values could have led to a higher harvest season wage at (2), implying a higher supply of labor in the planting season (and a lower demand for labor in the planting season), resulting in a final equilibrium at (3’). In all cases x_{1G} increases.