Forecasting Profitability[1]

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Abstract

We explore how improving the skill of long-range monsoon forecasts affects farmer investments and profitability. Based on panel data from India we show that farmers respond to government forecasts, that these responses account for much of the inter-annual variability in investments, and that farmers respond more strongly to the forecast where there is more forecast skill. We also show that the return to such investments depends substantially on the conditions under which it is obtained by estimating how returns to planting-stage investments induced by variation in forecasts vary by rainfall realizations. We find that farmers with access to skilled forecasts experience increased mean profits and less variable profits and show that improved forecast skill can substitute for weather index insurance.

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1. Introduction

It is well-established that agricultural profits in developing countries depend strongly on weather realizations. It is similarly well-known that farmers without access to good insurance markets act conservatively, investing less on their farms and choosing crop mixes and cultivation techniques that reduce the volatility of farm profits at the expense of lower expected profits. Economists have focused valuable attention on policies and programs that can provide improved *ex post* mechanisms for dealing with the consequences of this variability. For example, innovations in insurance can spread risk across broader populations, or improved credit or savings institutions can permit more effective consumption-smoothing over time. Innovations of this type can mitigate the consequences of risk, and therefore permit farmers to make riskier, more profitable decisions. Agricultural scientists have worked to improve the *ex ante* options available to farmers faced with uninsured weather risk, most prominently by developing drought-tolerant varieties of important crops.

Economists, however, have paid little attention to how farmers' capacity to deal with weather fluctuations is affected by the accuracy of forecasts of inter-annual variations in weather. 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 a risk-neutral or perfectly-insured farmer. The profit and welfare gains associated with improvements in the accuracy of long-range forecasts (forecasts that cover, for example, an entire growing season) are potentially enormous, given the tremendous variability in profits and optimal investment choices across weather realizations.[2] While there is no obvious market failure for weather index insurance, the information generated by an accurate

[2] Existing qualitative research in Tamil Nadu, Burkina Faso, and Zimbabwe suggests that farmers demand and respond strongly to information about future rainfall realizations (Ingrama *et al*. (2002); Phillips *et al.* (2002); Huda *et al*. (2004)).

weather forecast is a classic public good. Even if forecasts are demanded by farmers, they will be underprovided by private forecasters.

Governments are aware of and responding to this opportunity. For example, 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.[3] 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.[4] Despite these sums devoted to improvements in forecasting skill, we know of no estimates of farmers' responsiveness to forecast by forecast skill or of the profitability of improving the accuracy of long-term forecasting.

Economists have sought to quantify the impact of imperfect protection from risk, other market imperfections, or interventions designed to overcome such problems by estimating returns on investments. Estimates of these returns, however, have rarely (if ever) taken into account variability due to weather or other stochastic events that are common to all firms or farms. Well-identified studies that show the profitability of an investment or technological innovation or the return to an intervention are typically based on data from a single season in a particular locality and hence are conditional on a single realization of weather or other correlated shocks.[5] This issue is most salient for

[3] 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.

[4] For example, "Laxman Vishwanath Wadale, a 40-year-old farmer from Maharashtra's Jalna district, spent nearly 25,000 on fertilizers 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).

[5] When studies do extend over multiple periods, none have examined the sensitivity of returns to realizations of weather (Duflo *et al.* (2011), Banerjee and Duflo (2008), Banerjee *et al* .(2013),

agricultural production. Because of weather variability and other sources of aggregate risk, the standard errors associated with the estimated coefficients may substantially overstate the precision of the return estimate.[6]

We show in a simple theoretical model in which the sensitivity of farm profits to rainfall affects the return to farm investment how risk-averse farmers optimally respond to information provided by long-range forecasts about future rainfall realizations, and how these responses vary by risk, wealth and the skill of the forecast. The empirical work is based on the history of long-range forecasts from the IMD, combined with panel data from two sources: ICRISAT (2005-2011) and REDS (1996-2006) containing village-level time-series of rainfall.

We first estimate the skill of the IMD forecasts and show that there is wide variation across India in the correlation between the monsoon forecast and July-September rainfall realizations. We find that the IMD forecast has predictive power in a subset of the ICRISAT villages and a subset of districts across India as a whole. Consistent with that, we find that planting-stage investments in both the ICRISAT and the REDS samples respond more strongly to the forecast where it has more skill. This estimate of the effect of forecast skill on the responsiveness of investment to the forecast is robust to cross-sectional variation in a variety of agricultural characteristics.

We estimate the returns to planting stage investments taking into account the effects of rainfall realizations on returns by exploiting the multi-year observations on profits and rainfall. We use an instrumental variables strategy in which the forecasts issued by the IMD before planting affect planting-stage investments, but do not influence profits conditional on realized rainfall except via these investments. Our IV estimates of the profit function indicate that over the support of the rainfall distribution

Bloom *et al*.(2013), de Mel *et al.* (2008, 2009), Mobarak and Rosenzweig (2013), Karlan *et al.* (2013), Fafchamps *et al.* (2011), Udry and Anagol (2006)).

[6] For larger scale research projects spanning a wide range of geographical locations a variety of weather realizations may be realized, but there will be a concern that the weather realizations may be correlated with unobserved features of the locality that influence the returns to the investment. Most obviously, rainfall realizations will be correlated with the rainfall distribution, which typically will be related to agricultural returns (Duflo and Udry 2004).

in the ICRISAT villages, profits increase as investments increase. ICRISAT farmers thus dramatically underinvest. Our profit function results also show that the returns to investment are extremely sensitive to rainfall realizations.

In the penultimate section of the paper we use the estimates of the effects of the forecast and forecast skill on planting-stage investments and our estimates of the profit function, coupled with the parameters of the IMD forecast and actual rainfall realizations, to quantify the contribution of the forecast to investment variability and returns. We show that expected farm profits are increasing in forecast skill, and that profit variability declines with skill. We compare the gain to farmers from increased forecast skill to that found for farmers who obtain commercially-available weather insurance. We conclude with a discussion of the implications of our findings for the market for agricultural insurance.

2. Modelling Weather Risk, Forecasts, and Farming Choices

Two essential characteristics of agriculture are that output and the returns to agricultural investments are heavily dependent on weather shocks and second, that the agricultural production process takes place over time. Farmers must choose inputs before the realization of shocks which affect the productivity of those inputs. Revelation of updated information about the probability distribution of the current year's shocks will change farmers' optimal input choices. This is true for profit-maximizing farmers, and *a fortiori* so for risk-averse farmers lacking access to complete insurance markets. In this section we provide a simple model of farmer decision making that clarifies how changes in information generated by weather forecasts influence input choices, and how improvements in forecast skill affect input choices, profits and welfare.[7]

Consider a farmer who makes decisions about farm inputs (x_0) in the planting period *0* and additional inputs (x_1) in the harvest period *1*. The farmer realizes a harvest

[7] The model builds on Sandmo (1971), Newbery and Stiglitz (1981, chapter 6) and Fafchamps (2003) by adding forecasts and multiple stages of production.

in period *1*. In the harvest period, there are two possible states, $S \in \{b, g\}$ with $prob(S = b) = \pi$. Output $h_s(x_0, x_1)$ depends on the input choices and the realized state. We assume that $h_b(x_0,x_1) < h_g(x_0,x_1)$ and $\frac{\partial h_b(x_0,x_1)}{\partial x_t} < \frac{\partial h_g(x_0,x_1)}{\partial x_t}$ for $t \in \{0,1\}$ for all (x_0,x_1). Our assumption that output is less in the bad state than in the good state for any levels of planting and harvest stage inputs is not particularly restrictive in the context of Indian agriculture. The assumption that the marginal products of both planting and harvest stage inputs are higher in the good state depends on the particular inputs we are examining. For example, this assumption might be reversed for irrigation investment, which is not a component of the inputs we measure.[8]

To highlight the role of risk, we assume that credit and saving markets work smoothly; the farmer can borrow to finance inputs or save at the same risk-free interest factor *r*. Denote net saving by *a* and the farmer's initial wealth by *Y*. Although credit markets work well, we assume that insurance is incomplete; farmers face uninsurable risk from the realization of weather. The budget constraints are

(1) $$c^0 = Y - x_0 - a$$

(2) $$c_s^1 = h_s(x_0, x_1) - x_1 + ra$$

Before making input decisions in period 0, the farmer receives a forecast of the state to be realized in period *1*. The forecast is either B or G. Let *prob(S=b|B)=prob(S=g|G)=q*, so that *q* is the *skill* of the forecast.[9] We assume that the farmer knows *q*.[10] The realized

[8] Our assumption is that the marginal products of the aggregate planting stage input and the aggregate harvest stage inputs are greater in the good state than in the bad state. It may be that particular inputs (e.g., a drought-resistant seed) may be more productive in a bad state than in a good state; this is not inconsistent with our assumption that that aggregate input is more productive in the good state.

[9] We show that the forecast of the IMD exhibits this symmetry property: the accuracy of the forecast does not depend on whether it is a forecast for good or bad rainfall.

[10] We leave for future research the interesting question of how farmers learn the skill of the forecast (Miller (2013) examines farmers' interpretation of forecasts; and Taraz (2013) has a related investigation of farmer learning about evolving weather patterns).

state is known to the farmer at the time he or she chooses x_1. The key distinction between x_0 and x_1 in our model is that by the time period *1* inputs are chosen, the realized state has been revealed.

In period *1*, the farmer's problem is to choose

$$x_1^*(x_0, s) \equiv \arg\max_{x_1} h_s(x_0, x_1) - x_1.$$

Therefore we can define

$$f_s(x_0) \equiv h_s(x_0, x_1^*(s, x_0)) - x_1^*(s, x_0)$$

with $f_b(x_0) < f_g(x_0)$ and $\frac{\partial f_b(x_0)}{\partial x_0} < \frac{\partial f_g(x_0)}{\partial x_0}$ for all *x*. Conditional on the receipt of forecast $F \in \{B, G\}$ the farmer's period *0* decision problem is

(3) $$\max_{x_0, \mathrm{a}} u(c^0) + \beta\left(\mathrm{prob}(S = b \mid \mathrm{F})u(c_b^1) + \mathrm{prob}(S = g \mid \mathrm{F})u(c_g^1)\right)$$

subject to (1) and (2), and the usual non-negativity constraints on $x_0, c^0,$ and c_s^1, which will never bind because we make Inada assumptions on *u(.)* and $f_s(.)$.

In Propositions 1-3 in the Appendix, we confirm that risk-averse farmers without access to insurance markets choose lower levels of inputs than would a profit-maximizing farmer, that input use increases (and net savings decreases) when the forecast is for good weather and that this increase in input use increases with the skill of the forecast. [11] These propositions follow from the facts that planting-season inputs are more risky than the alternative asset and that the marginal product of planting-season inputs is higher in good than in bad weather.

Some dimensions of farmer heterogeneity are particularly salient for understanding how rainfall forecasts and their accuracy influence cultivation decisions. Propositions 4 through 6 show that input use increases in farmer wealth and decreases in riskiness of the environment. We also show that the responsiveness of investment to

[11] All propositions and proofs are provided in the appendix.

forecasts declines in the installed base of irrigation, and varies by farmer wealth and the riskiness of the environment.

We show in Proposition 7 that expected profits and expected utility increase with forecast skill. Expected profits increase with forecast skill for two reasons, as can be seen in (4):

$$
\begin{aligned}
&\frac{dE(profits)}{dq}\cdot 2 = \left[f_g(x_0(q|G)) - f_b(x_0(q|G)) \right] + \left[f_b(x_0(q|\mathrm{B})) - f_g(x_0(q|\mathrm{B})) \right] \\
(4)\qquad &+\frac{dx_0(q|G)}{dq}\left\{ q\left[\frac{\partial f_g(x_0(q|G))}{\partial x_0} - r \right] + (1-q)\left[\frac{\partial f_b(x_0(q|G))}{\partial x_0} - r \right] \right\} \\
&+\frac{dx_0(q|B)}{dq}\left\{ q\left[\frac{\partial f_b(x_0(q|B))}{\partial x_0} - r \right] + (1-q)\left[\frac{\partial f_g(x_0(q|B))}{\partial x_0} - r \right] \right\} \\
&> 0
\end{aligned}
$$

First, improved forecasts permit the farmer to match his input choices to the realized state. These are the first two terms in (4), which sum to a positive because $x_0(q|G) > x_0(q|B)$. These terms would be the same for a risk neutral farmer who simply maximizes profit. Second, improved forecast skill reduces the risk faced by the farmer. The reduced risk permits a risk-averse farmer to increase investment, on average, reducing the gap in the expected marginal product of investment in inputs and the return on the risk free asset. These are the second two terms in (4).[12]

3. Data

We use two panel data sets. There are two key features of these data for our purposes – information on investments by stage of production or time-period and time-

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[12]See the appendix for the full proof. This proposition relies on an additional assumption that the unconditional probability of bad weather is 0.5. The simplification associated with this assumption is that if and only if $\pi = .5$, the probability of a Bad (Good) forecast is invariant to changes in forecast accuracy. This is a consequence of our use of *q* to summarize forecast accuracy symmetrically for forecasts of good and bad weather. In general, $\frac{d\,\Pr(\text{Bad Forecast})}{dq} = -\frac{2\pi - 1}{(2q-1)^2}$ and changes in *q* can't be modelled independently of changes in the actual probability of bad forecasts.

series of village-level rainfall. The stage-specific investment data enable us to measure the *kharif*-season planting-stage investments (the value of labor used in plowing, seeding and fertilizing plus the costs of the material inputs) 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. The rainfall time-series permit us to compute various time-specific measures of rainfall shocks for the assessment of forecast skill and to estimate the sensitivity of investment returns to rainfall outcomes that are not attenuated due to the lack of proximity of rainfall gauges to the sample respondents.[13]

The first set of data is from the ICRISAT Village Dynamics in South Asia (VDSA) surveys for the years 2005-2011 in the six villages from the first generation ICRISAT VLS (1975-1984). The villages are located in the states of Maharashtra (4) and Andhra Pradesh (2). These data provide daily rainfall for each of the six villages for as long as 30 years and are collected at a high frequency so that accurate information is provided on the value of inputs by operation and by date as well as the season-specific profits associated with those investments.[14] We use these data to estimate both the response of planting-stage investments to the IMD forecasts and the returns to such investments under different weather conditions.

The second panel data set we use is from the 1999 and 2007-8 Rural Economic and Development Surveys (REDS) administered by the National Council of Economic

[13] Many studies estimating rainfall effects use the University of Delaware Air Temperature and Precipitation Data set, which provides climatologically-aided spatial interpolations of monthly rainfall for a set of points on a 0.5 degree by 0.5 degree latitude/longitude grid based on a limited set of weather stations (http://climate.geog.udel.edu/~climate/html_pages/Global2011/README.GlobalTsP2011.html). The rainfall time-series for the grid points are subject to interpolation error, and the correlation between these supplied data points and actual rainfall for any point (village location) within the grid may be quite small, given the strong negative association between distance and the rainfall correlations between any two villages found by Mobarak and Rosenzweig (2013) using monthly village-specific rainfall time-series data.

[14] Dates of operations are not always provided so that certain operations such as fertilizing, included in our measure of planting-stage investment, may have occurred in some cases after the realization of early-season rainfall. In the estimation of the profit function we control for rainfall during the entire *kharif* season so that identification of the effects of planting-stage investments is based on variation solely induced by forecast changes. We also assess if our estimate of the forecast on measured investments is sensitive to the inclusion of post-forecast rainfall.

Research (NCAER) in 242 villages in the 17 major states of India. This survey, like the ICRISAT survey, elicited information on inputs by season and stage of production so that it is also possible to construct a measure of *kharif* planting-stage investments. The data set also includes monthly rainfall information at the village level for 212 villages covering the years 1999-2006. Given the wide spatial coverage of the REDS, these rainfall data enable us to estimate the skill of the IMD forecasts across Indian regions and thus to estimate if and how planting-stage investments respond differentially to forecast skill conditional on other regional characteristics for 2,219 farmers. A limitation of the data is that 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 returns to planting-stage investments that account for the effects of rainfall variability.

The top and bottom panels of Table 1 provide descriptive statistics for the ICRISAT and REDS data. As can be seen, while the average planting-stage investments in both surveys is comparable, there is substantially more investment variation in the REDS data set, reflecting its wider geographic scope. The shape of the distribution of investments is similar across the data sets, and is well characterized by the log-normal distribution.[15] Another notable difference in the two data sets is that the intertemporal coefficient of variation in crop-year rainfall in the ICRISAT villages is double that for the average for the more representative sample of farmers in rural India. The fraction of land that is irrigated for ICRISAT farmers is also 26% lower than that of farmers in the REDS. Rainfall variability is thus an especially salient issue for the ICRISAT farmers.[16]

[15] Appendix Figures 1-4 display the planting-stage and the log planting-stage distributions from both data sets. Given these distributions, we will employ the log of planting-stage investments when we estimate the determinants of those investments.

[16] Our measure of profits is the value of agricultural output minus the value of all agricultural inputs, including the value of family labor and other owned input services. 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 A1 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

4. 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 percentage 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. The 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.[17] 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.

What is the skill of the forecasts in predicting July-September rainfall?[18] 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 early years the forecasts are qualitative ("far from

10.6%. Therefore, we set *r=1* for the profit value in Table 1. We assess how our investment returns estimates differ when we allow discounting below.

[17]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).

[18] In the literature on forecasting, 'skill' is the term used for the accuracy of the forecast. The typical measure of skill is the correlation between the forecast and the realized weather (see, for example, Turner and Annamalai 2012).

normal”). Starting in 1999, 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 or for above-normal monsoon rainfall the likelihood the forecast is correct slightly above 50% in each case.

Forecast skill, however, may vary by region. In the period 1999-2003, the forecasts were issued for three regions of India. Starting in 2004, the forecasts have been issued for four broad regions of India (see Appendix Map A1). To estimate district-specific forecast skill, we obtained the correlations between the regional IMD forecasts and the village-specific times-series of rainfall in the ICRISAT and REDS data. For the ICRISAT data (2005-2011) we use the Southern Peninsula (SP) forecasts. For the REDS (1999-2006), we matched up the REDS village rainfall time-series with the appropriate regional forecasts over the time period. If there is indeed spatial variation in skill, we can use that variation to test a key prediction of our model, that the response of investments to the forecasts will be stronger the higher is forecast skill.

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.

The REDS data also show regional patterns of forecast skill. 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 in our estimates of skill could just be noise. However, there appear to be broad geographical areas where the skill is substantially higher and we can reject the null hypothesis that the forecast has no skill.[19] Map 1 shows where in India the correlations are highest (darker areas), with the Northeast area exhibiting the highest skill. Of course, the key question raised by Propositions 2 and 3 is whether farmers respond to the forecasts, and do so more strongly where the forecast has greater skill.

5. Rainfall Forecasts, Forecast Skill and Planting-Stage Investments

As shown in section 2, optimal input investment by household *h* in village *v* (x_{hvt}) depends upon the forecast (Proposition 2), F_{vt}, the interaction of the forecast with a set of fixed farm characteristics Z_{khv} that affect wealth and the riskiness of inputs (Propositions 5 and 6), lagged profits (Proposition 4), and forecast skill (itself interacted with the forecast, and with Z_{khv}) (Proposition 3). In addition, x_{hvt} depends upon lagged rainfall realizations via soil moisture overhang, and this effect may vary across farmers depending on Z_{jhv}, most importantly soil depth (which changes the extent of moisture overhang). It also is important that we control for lagged rainfall (R_{vt-1}) in case the IMD forecast partly depends on rainfall history. We are examining early season, planting-stage input investments to ensure that these decisions do not depend upon later season rainfall realizations (this assumption is tested below). Log planting stage input investments by household *h* in year *t* are therefore specified as

$$\begin{aligned} x_{hvt} = {} & F_{vt} \cdot \left[\alpha_F + \alpha_{FF} F_{vt} + \sum_k \alpha_{kF} Z_{khv} \right] + R_{vt-1} \cdot \left[\alpha_r + \sum_j \alpha_{jr} Z_{jhv} \right] \\ & + \alpha_\pi \pi_{hvt-1} + q_v \alpha_q + F_{vt} \cdot q_v \cdot \left[\alpha_{qF} + \sum_k \alpha_{kq} Z_{khv} \right] + \lambda_{xhv} + \eta_{hvt}, \end{aligned} \tag{5}$$

[19] We use a Bonferroni correction (which permits arbitrary correlations between estimates of skill), which requires *p≤0.0002* to reject at the 5% level. This is a very conservative approach, because both the forecast and monsoon rainfall are positively spatially correlated.

where λ_{xhv} is a household fixed effect that may affect input choices, and η_{hvt} is a random shock uncorrelated with other determinants of input choice. The household fixed effect is collinear with the direct effect of forecast skill on investment, so α_q is not identified.

The first column of Table 3 reports farmer fixed-effect estimates from the ICRISAT panel data of a reduced-form version of the (log) planting-stage investment equation (5) in which we replace lagged profits by the previous year's monsoon forecast and initially omit the interactions between land characteristics and the forecast. The set of lagged rainfall and the contemporaneous forecast coefficients are statistically significant; the point estimate is that a one percentage point increase in the IMD rainfall forecast results in a 1.5% increase in planting-stage investments.

We make use of Proposition 3 to show that farmers are behaving in accord with the model. Proposition 3 implies that the ICRISAT farmers in Andhra Pradesh should not be responding to the IMD forecasts in making their planting-stage investments. As shown in Table 2, forecast skill in the Andhra Pradesh villages is nil, so unless farmers are unaware of the poor performance of the forecasts or we have incorrectly characterized forecast skill, a finding that planting-stage investments are substantially influenced by the forecasts in these villages would call into question our assumptions and/or model. The response of investments in the planting stage to the forecast should only be exhibited in the Maharashtra ICRISAT villages. The estimates of the planting-stage investment equation for the Maharashtra and Andhra villages are reported in columns two and three of Table 3, respectively. Consistent with the model, the effect of the forecast in the two Andhra Pradesh villages is not significantly different from zero and the point estimate is less than a third of that in the villages with forecast skill.[20]

[20] Another concern is that the measured planting-stage investments based on the ICRISAT data may reflect in part realized rainfall in the early months of the *kharif* season, which are correlated with the forecast, so that we are over-estimating the power of the forecast in influencing farmer decisions. To test this, we also included in the specification actual July-September rainfall (not shown). Actual rainfall was not a significant predictor of planting-stage investments, with an asymptotic t-ratio of 0.11, while the forecast coefficients retained their statistical significance and quantitative importance.

In columns 4-6 of Table 3 we provide estimates that include interactions of the forecast with itself and with six characteristics of the farmer's landholdings – total land size, share of land irrigated, and four soil types. As can be seen, the results are similar to those from the simpler specification, although now the full set of skill and skill interaction coefficients (not shown) are jointly statistically significant for all the villages and for the Maharasthra villages but not for the Andhra villages. The net effect of higher responsiveness of investment to forecasts in Maharashtra is that investment in Maharashtra is more variable. The average coefficient of variation of investment in the Maharashtra villages is 60%, while the average CV in Andhra Pradesh is 41% (these are statistically significantly different, *p=0.027*).[21]

There may be alternative explanations associated with unobserved heterogeneity at the village level that account for the sharp difference we observe in the effects of the forecast on planting-stage investment across the two ICRISAT areas. The REDS data, from which we have many more village-level estimates of forecast skill and many more farmers, allow us to estimate directly how forecast skill, as measured by the correlation between the IMD forecast and actual rainfall in the local area, affects the responsiveness of planting-stage investments to forecasts. We can also use the REDS data to assess the robustness of our forecast estimates to heterogeneity in farmers and geographic areas. We thus use the REDS data to estimate investment equation (5) excluding lagged profits (which did not seem to matter), given we only have two observations per farmer, but including the interactions between forecast, forecast skill and other characteristics of the region and farmer.

Column 1 of Table 4 reports farmer FE estimates of the effects of the IMD forecast and the forecast interacted with forecast skill on the log of planting-stage

[21] In Appendix Table A2, we replace the lagged forecast variable by lagged profits, treating that variable as endogenous and using the lagged IMD forecast and its square and the interactions of the lagged forecast with the farm land characteristics as instruments. The estimates of the forecast effects on investments are similar to those reported in Table 3, with again the forecast only having power in the Maharasthra villages. However, previous-year profits, net of the current forecast and rainfall overhang effects (which remain statistically significant), are not themselves significant predictors of investments made in the planting stage.

investments in the REDS data. Consistent with the model and with the investment estimates by state from the ICRISAT data, the response of the investments to the forecast is statistically significantly higher the higher is forecast skill in the area, and a higher forecast leads to more investments, though not statistically significantly so. One reason for the small average response to the forecast is that, as shown in Table 1, a large fraction of REDS farmers cultivate on irrigated land. Proposition 5 indicates that because irrigation reduces the losses from poor rainfall outcomes, planting-stage investments of irrigated farmers will be less responsive to increases in forecast skill. To test this, we added interactions between the fraction of the farmer's land that is irrigated and the forecast and forecast skill. The estimates for this specification, shown in column two of Table 4, are consistent with the model and the effects of irrigation on the sensitivity of investment returns - the higher the fraction of the farmer's land that is irrigated, the lower the responsiveness to forecast skill. This irrigation gradient is statistically significant, as is the effect of forecast skill on the forecast response for unirrigated farmers. The point estimates indicate that at a forecast skill of, say, .43 (the forecast skill in Shirapur village in the ICRISAT data for which we have the longest rainfall time-series) among unirrigated farmers a one percentage point increase in the forecast increases planting-stage investments by 9%. In column 3, we add a full set of interactions between the forecast, forecast skill and land characteristics of the farmer (these include the four soil types, total land owned, and the two soil depth indicators). The interactions are jointly statistically significant (*p=0.00*), but the main effects of the forecast and forecast-skill interaction are stable.

Village-level forecast skill may be correlated with other area characteristics that affect farmer investments. As was seen in Map 1, forecast skill has strong spatial patterns. One striking fact is that where the forecast skill is higher many farmers grow rice.[22] To assess if our finding of the higher responsiveness of investments to the

[22] This is shown in Appendix Map A2, based on the cropping patterns of the farmers in the REDS. It shows that in the northeast area with good forecast skill is one of the rice-intensive areas, defined as areas in which at least 75% of farmers grow rice.

monsoon rainfall forecast in high skill areas merely reflect the differential responsiveness of rice farmers to forecasts, we added interactions between the forecast and forecast-skill interaction and a dummy variable for whether the village was in a rice growing region. In addition, Proposition 6 shows that the riskiness of production will in general change the responsiveness of farmers to forecasts and to the skill of forecasts. Therefore, we added interactions between the forecast and forecast skill variables and a measure of the variability of village-level rainfall (CV), which also varies greatly across Indian regions (see Appendix Map A3). The fourth column of Table 5 displays these estimates. As can be seen, the set of rice coefficients are not statistically significant jointly or individually. The set of CV interaction coefficients is statistically significant at the 10% level, but the magnitudes and statistical significance of the coefficients associated with the responsiveness of investments to forecast skill for irrigated and unirrigated farmers are unaffected.[23]

In Table 5, we present estimates of the responsiveness of planting level investments of farmers in the REDS sample to the forecast at varying levels of forecast skill using an alternative to the correlation-based estimate of forecast skill. The mean rainfall of a village in the REDS sample is typically different from mean rainfall over the broad IMD region in which it is situated. We construct an estimate of the forecast skill in a particular district by adjusting for these mean differences:

$$R_{jk} = v_{jk} + \beta_j F_j + \varepsilon_{jk}, \tag{6}$$

where *j* indexes districts and *k* indexes villages. Our estimate of the skill of the forecast in district *j* is $\max\{\hat{\beta}_j, 0\}$. Column 1 of Table 5 presents reports farmer FE estimates of the effects of the IMD forecast and the forecast interacted with forecast skill on the log of planting-stage investments. As in the analogous specification reported in column one of Table 4 with the correlation-based estimate of skill, there is a positive response of

[23] We also estimated specifications adding mean rainfall interactions. These also were not significant determinants of planting-stage investments and did not alter the forecast skill estimates.

investment to forecasts only in districts with skill.[24] In column 2, we restrict attention to districts with positive estimated skill, to examine the possibility that we introduced a bias by truncating estimated skills at zero. For this subsample as well we see the same pattern: the responsiveness of investment to the IMD forecast is stronger in those districts in which the forecast has more skill.

One concern with estimating forecast response by forecast skill is that our skill measure is only an estimate of farmers' assessment of the skill of the forecast in their district, based only on seven years of village-specific rainfall. To take this into account, we maintain the assumption that farmers know β_j, but we have available only $\hat{\beta}_j$. We also have information, however, on the reliability of our estimates of district-specific forecast skill, namely the district-specific standard errors of $\hat{\beta}_j$. In column 3 of Table 5, we report the estimates corrected for this measurement error in forecast skill using the coefficient standard errors. As expected, this increases the point estimates of the responsiveness of investment to the forecast, and of the effect of the interaction between forecast skill and the forecast. Our conclusion remains unchanged: farmers respond to the IMD forecast by increasing investment only in those districts in which the forecast has skill.

6. Rainfall Variability and the Returns to Planting-Stage Investments

The REDS and ICRISAT data sets both suggest that farmers' planting-stage investments respond to the IMD forecasts, with such responses differing across farmers (for given forecast skill) depending on their specific land characteristics. We now use the IMD forecast as part of an IV strategy to estimate the returns to planting-stage investments. In particular, we estimate a conditional profit function using the ICRISAT panel data, treating planting-stage investments as an endogenous choice that responds

[24] Investment responds positively to the forecast in districts with $\hat{\beta}_j > 22.5$ (corresponding to a correlation between the forecast and actual rainfall of .22), which is the case for 40% of the districts with any skill in the REDS sample.

to the rainfall forecast. To identify investment returns, we have to impose additional structure to ensure that the forecast instruments satisfy the exclusion restriction.

Agricultural profits depend on investments in planting-stage inputs and on the realization of rainfall, and as our model has emphasized, on the interaction between these. In addition, agricultural profits are functions of a number of dimensions of heterogeneity, such as farm size, soil characteristics, and irrigation and interactions of these with rainfall. There is also good evidence (Sharma and Acharya 2000) that profits depend as well on lagged rainfall (differentially depending upon farm characteristics, particularly soil depth) through the soil moisture overhang effect. Hence we specify a linearized version of the farm profits of household *h* in village *v* in year *t* that is quadratic in planting-stage investments as

$$\begin{aligned}\pi_{hvt} &= \beta_x x_{hvt} + \beta_{xx} x_{hvt}^2 + R_{vt} \cdot \left[\beta_r + \beta_{rr} R_{vt} + \beta_{rx} x_{hvt} + \beta_{rxx} x_{hvt}^2 + \sum_k \left(\beta_{rk} Z_{khv} \right) \right] \\ &+ R_{vt-1} \cdot \left[\beta_{rl} + \beta_{rrl} R_{vt-1} + \sum_k \left(\beta_{rkl} Z_{khv} \right) \right] + \lambda_{\pi vt} + \lambda_{\pi hv} + \varepsilon_{hvt}.\end{aligned} \tag{7}$$

$\lambda_{\pi vt}$ is a village-year fixed effect that absorbs time-varying village-specific input prices (particularly wages) that could be correlated with rainfall forecasts. $\lambda_{\pi hv}$ is a household fixed effect, and ε_{hvt} is a shock to farm profits. A key feature of (7) is that the effects of planting-stage investments on profits depend on the realization of rainfall R_{vt} This is, of course, central to any model in which rainfall risk has consequences for income and investment choices.

Excluded from (7) are the rainfall forecast (F_{vt}) and its interactions with exogenous fixed land characteristics. This is the primary identification assumption required to estimate the returns to planting-stage investments. That is, conditional on realized rainfall, the forecast of total rainfall in the monsoon affects profits only through its effect on x_{hvt}. There are three primary concerns regarding this excludability assumption. The first is that that conditional on our specific measures of realized rainfall, the forecast of total rainfall may be correlated with an unmeasured dimension of rainfall that matters for profits. As described in section 3, we measure realized rainfall as the total amount of rainfall over the year and the total amount of rainfall over the monsoon, as the IMD long-range forecast is the prediction for the total amount of rainfall over the monsoon. Binswanger and Rosenzweig (1993) have shown that the monsoon onset date is a salient feature of rainfall for farm profits in India. However, in the ICRISAT data we find that conditional on even a subset of our measures of rainfall (monsoon rainfall), the IMD forecast of total monsoon rainfall is not correlated with the onset date.[25] We include both the monsoon onset and end dates, calculated from the daily rainfall information, interacted with land characteristics in the profit-function specification.

Second, the rainfall forecast for a given year is common to everyone in a village. Through its effect on input demand, a forecast of good (bad) weather could raise (lower) input prices – particularly wages – in a village. In principle it is possible as well that there could be policy interventions (changes in regulated grain prices, emergency agricultural interventions, *ex ante* efforts to provide relief). These village-specific changes correlated with the forecast could affect profits directly. As noted, the village-year fixed effect $(\lambda_{\pi vt})$ is included in (7) to address this possibility. A casualty of including village-year fixed effects is that the direct effects of rainfall and lagged rainfall on profits are not identified.

A third concern that would make the forecast non-excludable in (7) is that the increased planting-stage investments induced by a favorable forecast reduce the farmer's resources available for subsequent production stages. In the model this was ruled out by the assumption of perfect credit markets within the season. That is, farmers are able to profit-maximize conditional on their planting-stage investments. We will provide a test of this assumption below.

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[25]We find $\underset{}{Onset_{vt}} = \underset{(3.47)}{370} \; \underset{(7.47)}{-.139MR_{vt}} \; \underset{(0.86)}{-1.064F_{vt}}$. Absolute values of asymptotic *t*-ratios in parentheses.

Table 6 reports fixed-effects instrumental variable (FE-IV) estimates of the profit function (6), with the FE at the farmer and village-year levels. The IMD forecast interacted with the characteristics of the farm and farmer are the instruments for planting-stage investments. All profit function specifications include current-year and prior-year annual and July-September rainfall; monsoon start and end dates; the squares of the rainfall quantity variables; the rainfall variables interacted with total landholdings, irrigated landholdings, soil depth, and four soil types (red, black, sandy, loam); and annual rainfall interacted with the planting-stage investment variable.

The first two columns of Table 6 report profit specifications that are linear and quadratic in investment, respectively, and that exclude the village/year fixed effects, but in which the effects of the planting-stage investments depend on rainfall. For either specification we can strongly reject the hypotheses that (i) larger planting-stage investments do not increase profits over almost the full range of the investment distribution in the sample and (ii) investment returns do not depend on rainfall. The same conclusions follow in the quadratic specification when we include the full set of village/year dummies to absorb any aggregate effects of the forecast on input prices (column 3).[26] These estimates imply that *ex-post* optimal investments depend on realized rainfall outcomes, or, put differently, how much underinvestment one would infer from profit function estimates depends on what is assumed to be the typical rainfall outcome. Investment returns also remain concave when we include the village-

[26] The F(9, 1724)-statistics for the set of identifying variables including the forecast, the forecast squared, the and the forecast interacted with total landholdings, with irrigated landholdings, with July-September rainfall, with annual rainfall and with annual rainfall interacted with landholdings and irrigated landholdings are, for the four endogenous variables (preparation investments, preparation investments squared, preparation investments interacted with annual rainfall, and preparation investments squared interacted with annual rainfall) 8.19, 10.17, 6.74, and 7.63, respectively, all significant at the .0001 level. The Anderson (1951) canonical correlations test statistic strongly rejects under-identification for all specifications (except for the sample of farmers in the low-skill villages (column 4)). For example, the test statistic, $\chi^2(33)$, = 73.4 (*p*=.0001) for the column-3 specification. The full set of first-stage estimates is available upon request from the authors.

year fixed effects and we also cannot reject the hypothesis that the point estimates of the coefficients of investment, investment squared and their interactions with rainfall and rainfall-squared are the same in columns 2 and 3.[27] The estimates in columns 1-3 imply that at mean levels of investment in the ICRISAT sample, returns to planting-stage investment are positive over the full range of rainfall realizations observed in the data. Figure 1 confirms this result for both the linear and quadratic specifications, while permitting the return to vary non-parametrically with rainfall.[28]

Although for the whole panel sample our instruments have power, to ensure that identification of the profit-function estimates is based on the investment forecast response we separately estimate (7) for the sample of farmers in the Andhra Pradesh and Maharasthra villages. These estimates are reported in columns 4 and 5 of Table 6, respectively. As expected, for the sample of farmers in the Andhra Pradesh villages where there is no forecast skill and little investment response to forecasts we cannot obtain any statistically significant effect of planting-stage investments on profits and the under-identification test fails to reject,[29] while the estimates of investment effects are statistically significant for the Maharasthra farmers and similar to those obtained from the whole sample.

The profit estimates reported in the columns 1 through 5 were based on a measure of annual profits assuming a zero discount rate, consistent, as noted with real interest rates in our sample. To assess the robustness of the profit-function results to this assumption, we re-calculated profits assuming an annual discount rate of 10%. The

[27] The $\chi^2(4)$ test statistic is 4.74 (p=0.31). The robustness of the profit-function estimates to the inclusion of the village/year fixed-effects is consistent with our finding that the IMD forecasts have a statistically significant but small effect on planting-stage wages (Rosenzweig and Udry, 2014).

[28] Figure 1reports the locally smoothed FE-IV estimates of the return to planting-stage investment using the specifications reported in Table 6, Columns 1 and 2 at each rainfall realization. The return is the derivative of profits with respect to investment, estimated at the ICRISAT sample mean investment, at each level of rain. The tricube kernel is used, with a bandwidth of 0.7.

[29] The relevant test statistic, $\chi^2(30)$, = 31.1 (p=.41).

estimates using this profit measure obtained from the Maharasthra- village sample are reported in column 6 of Table 6. As can be seen, the estimates are largely unchanged from those obtained using a zero discount rate.

Finally, as noted, the excludability of the forecast instruments from (7) assumes that farmers can freely maximize profits conditional on their planting-stage investments. The ICRISAT survey data enable us to carry out a global separability test similar to that of Benjamin (1992). The basic idea is that exogenous changes in the family labor force should not affect profits if all input markets are unconstrained. Changes in household size or in labor supply are not obviously exogenous to profit changes. However, illness has a large random component (net of the household fixed effect), and illness can affect the family's ability to supply labor.

For the years 2005, 2006, 2010 and 2011 the ICRISAT survey elicited information on the number of days that adult family members were ill in the *kharif* season. Household fixed effect estimates obtained for the total sample of farmers and the farm households in the Maharasthra villages in those years of the effect of the number of sick days on total labor days in the *kharif* season, reported in Appendix Table A4, indicate that for each day an adult was sick almost a third of a day of on-farm family labor was lost. The estimates are highly statistically significant. If liquidity constraints limited the ability of the household to substitute hired labor to make up for family labor days lost, an increase in sick days should therefore decrease profits. In the last column of Table 6 we report FE-IV estimates of the profit function for the Maharasthra farmers including the number of adult sick days. As can be seen, we cannot reject the hypothesis of separability – despite sick days evidently significantly reducing on-farm family labor supply -- an increase in the number of adult sick days has no impact on profitability.[30]

To see what our estimates imply for the sensitivity of returns to rainfall realizations and for assessing the degree of underinvestment we plot in Figure 2 the relationships between profits and investments for rainfall at the mean and at the

[30] Note that it is plausible that shocks to profits affect illness. However, this would create a negative bias for the sick days coefficient. Thus, we have a statistically strong test of separability.

minimum, maximum and 75th percentile of the actual rainfall distribution in the ICRISAT villages. We use the estimates in column 2, without village-year fixed effects, to include the direct effect of rainfall realizations on profits.[31] The mean, the 10th and the 90th percentiles of the distribution of planting-stage investment in the ICRISAT sample are indicated on the investment axis. We note three important features of this figure.

First, the return to a given investment varies substantially depending on the rainfall outcome. For example, an additional R10,000 investment (over the base of R12,000) would have an estimated return of about R10,000 in additional profits if estimated in a year of rainfall at the minimum of the distribution. However, the same investment would have a return of over R50,000 if estimated using data from a year in which rainfall was at its maximum. This illustrates that an estimate in one place at one time of the returns to investment has a precision that is much smaller than that indicated by the *t*-ratios of the coefficients if the influence of rainfall variability is ignored.[32] This feature of Figure 2 also demonstrates the challenges involved in attempting to generalize results from studies of agriculture undertaken in limited geographical range. If the plots by rainfall realization represent averages for different areas, rather than the stochastic outcomes of one area, our estimates indicate that estimates obtained at different places would provide very different estimates of returns to investment just from rainfall heterogeneity.

A second feature of the figure is that there is considerable underinvestment. Profits are not only increasing with planting-stage investment at the actual mean investment level observed in the sample, consistent with Proposition 1, but for every observed rainfall outcome over almost the entire distribution of observed planting-stage investments. Underinvestment is sufficiently ubiquitous that even at the 90th percentile of observed investment, profits are increasing, even at the minimum observed rainfall.

[31] Were we to use the (statistically-indistinguishable) estimates with village-year fixed effects instead, the intercept of each curve would be arbitrary. Comments 1 and 2 which follow are independent of any such normalization; comment 3, however, relies on the estimates of the direct effect of rainfall on profits.
[32] We quantify this difference in Section 7 below.

Finally, a third feature of Figure 2 is that rainfall risk at the mean level of investment observed in the ICRISAT sample is small relative to the risk at higher levels of investment.

7. The Profitability of Improving Forecast Skill

We have seen in Tables 3-5 that in villages in which the forecast is more strongly positively correlated with rainfall outcomes, farmers respond more powerfully to the forecast by increasing (decreasing) planting-stage investments when the forecast is for more (less) rain. We have also shown that the return to these planting-stage investments is higher when realized rainfall is higher. Proposition 7 states that expected profits should rise with forecast skill. Our estimates of the profit function and the input demand function can be combined with information on the joint distribution of rainfall realization and forecasts to provide estimates of the effects of changes in forecasting skill on the distribution of farm profits.

Farm profits are a concave function of planting-season investments interacted with rainfall realizations. As a consequence, expected profits are not a simple function of expected rainfall, expected forecasts, and the expected value of planting-stage investments. In order to describe the distribution of profits, we simulate profits using repeated draws from the joint distribution of rainfall and forecasts for a typical farmer, subject to varying assumptions regarding the skill of the forecast. As the baseline for the simulations, we use the mean values of farm characteristics and the rainfall distribution in the ICRISAT village of Kinkheda, which has a relatively low baseline forecast skill of 0.2.[33] We use the parameter estimates of the coefficients in equations (7) and (5) to

[33] The correlation matrix for total rainfall (mm), monsoon rainfall (mm), the monsoon start date (days since Jan 1) and the IMD forecast (% of normal) for Kinkheda is $\begin{pmatrix} 1 & .9807 & -.2318 & .1961 \\ .9807 & 1 & -.1881 & 0.2 \\ -.2318 & -.1881 & 1 & -.0376 \\ .1961 & 0.2 & -.0376 & 1 \end{pmatrix}$. As the simulations increase the correlation between monsoon rainfall and the IMD forecast, we assume that the correlation between the total rainfall and the forecast and monsoon onset and the forecast change proportionally, while of course the correlations between total and monsoon rainfall and monsoon onset are fixed.

generate a prediction of planting-stage investment, and (using the predicted planting-stage investment) farm profit. We then trace out the consequences for the distribution of profits of increasing skill from 0.2 to 0.6.

To generate predicted planting-stage investment as skill increases, we use the consistent estimate of α_{qF} from equation (5) reported in column 1 of Table 4. α_q is not identified, however, because it is collinear with the household fixed effect. Therefore, we simulate a lower bound responsiveness of investment to increases in skill by setting $\alpha_q = -\alpha_{qF} * 100$ so that at a forecast of normal monsoon rainfall (*F*=100), investment does not change as forecast skill increases. This is a lower bound because, as we have shown in Proposition 7, planting-stage investment would actually increase on average as forecast skill improves (and there is underinvestment, so profits increase on average with investment). For each realization of the IMD forecast we generate a prediction of planting stage investment. The predicted planting stage investment is combined with corresponding draws of total rainfall, monsoon rainfall and monsoon onset date and the parameter estimates of equation (7) from column 2 in Table 6 to generate predicted profits for each realization of rainfall and IMD forecast.[34]

The simulation results are presented in Figure 3. The solid line represents the mean of the distribution of profits across these rainfall/forecast realizations for the typical Kinkheda farmer. As noted, we have imposed the assumption that on average planting-stage investments remain constant as forecast skill increases. Therefore, the upward slope of expected profits is due entirely to the better match of planting-stage

[34] Estimates of the standard error of the forecast profits are generated from 1000 bootstrap iterations. In each iteration, independent bootstrap samples are drawn from the REDS and ICRISAT samples. Equation (5) is re-estimated from the REDS bootstrap sample by OLS, imposing the constraints that $\hat{\alpha}_{qF}$ remain fixed at its consistent estimate from column 1 of Table 4 and $\hat{\alpha}_q = -100\hat{\alpha}_{qF}$. Equation (7) is re-estimated from the ICRISAT bootstrap sample by IV as in column 2 of Table 6. The constrained estimates are reported in Appendix Table 5. Predicted profits for each skill level are generated for each of the same 10,000 simulated rainfall and forecast realizations, as described in the preceding paragraph. The estimates of the standard error of predicted profits for each rainfall realization is the standard deviation of the predicted profits across the 1000 bootstrap samples.

investment to later rainfall realizations enabled by improved forecast skill. Were investment to increase with better forecast skill, as implied by proposition 7, average profits would increase more steeply because (as we have shown in Figure 1) profits are increasing in investment for the typical farmer over the entire rainfall distribution.

The upper dotted line is the standard deviation of profits across rainfall and forecast realizations for each level of forecast skill. As can be seen, as forecast skill increases, not only do average profits increase, but variability in profits due to rainfall variability decreases. The lower dashed line is the standard deviation of predicted mean profits across bootstrap samples, the statistical standard error of our profit estimate. As can be seen, the variation in profits due to weather variability and forecast outcomes is approximately twice that of the estimation error. As we noted in our discussion of Figure 2, an estimate of profits conditional on a single realization of weather (and forecast) has in fact far less precision than would be indicated by the standard error of that estimate conditional on that weather realization.

How does increasing forecast skill compare with alternative approaches to improving the risk management environment of farmers? Cole *et al.* (2013) examines the effect on agricultural investment of providing grants of rainfall index insurance to farmers in Andhra Pradesh. Farmers receiving the insurance grant evidently increased their investment by approximately 8% relative to the control group.[35] We again use our estimates of the parameter values of equation (7) from column 2 of Table 6 to estimate the effect on profits (net of insurance payouts minus the actuarially fair value of the insurance policy) of an 8% increase in investment for a typical farmer in one of these villages, over 10,000 simulated rainfall draws. To carry out the simulation, we use the characteristics of the average farmer in a village in Andhra Pradesh (the state in which the insurance grants were provided), Aurepalle, and also use the parameters of the

[35] Cole et al. (2013), Table 3. The estimate of the difference (0.082, se=0.087) is not significant at conventional levels, and investments are not disaggregated by cultivation stage. We use it as the best available estimate of the responsiveness of investment to formal insurance in India.

Aurepalle rainfall distribution.[36] Because the baseline forecast skill in Aurepalle is zero, planting-stage investment is constant across the simulated rainfall draws.

The first column of Table 7 reports the baseline mean profit and standard deviation of profits across the simulated rainfall realizations of the typical farmer at the mean investment observed in Aurepalle with no rainfall index insurance, and a forecast skill of 0. In column 2, we see that the 8% higher investment associated with access to rainfall index insurance generates 3% higher profits on average (we assume that the insurance is actuarially fair, so the net flow of insurance payouts minus the cost of insurance is zero on average). The insurance is effective in reducing the variability of profits net of insurance flows. In column 3, we report the results of simulating the effect of increasing forecast skill in Aurepalle from 0 to 0.45 (the highest skill observed in the ICRISAT villages), instead of providing insurance. This simulation uses the same procedure described above for assessing forecast profitability, but applied to a farmer with the mean characteristics of those in Aurepalle. We find that this increase in forecast skill generates a (lower-bound) increase of 6% in average profits, double that from the insurance contract, and that the standard deviation of profits is also smaller than that obtained through index insurance. There is a catch, however, to this superior performance: in 14% of the years, profits are lower than those realized in the absence of a forecast due to an erroneous optimistic forecast.

8. Conclusion

The existence of agricultural risk implies that farmers would benefit from improved signals of future rainfall realizations. Long-term forecasts of monsoon rainfall have been issued by the Indian government for many years. We used newly-available panel data on farmers in India to assess the ability of the rainfall forecasts to predict

[36] Aurepalle is the ICRISAT village in Andhra Pradesh for which we have the longest observed series of rainfall. In order to simulate insurance payouts, we used the daily rainfall recorded by ICRISAT to calculate the cumulative rainfall during the 35 days after the monsoon start as defined in the ICICI Lombard insurance policy and described in Cole et al. (2013). The actuarially-fair value of the insurance provided in the experiment was Rs.350. To match that actuarially fair value given the Aurepalle rainfall distribution, we set the "strike" to 0 and the "exit" to 8.

rainfall, the responsiveness of farmers' investments to the forecasts, and how the returns to planting-stage investments vary by rainfall realizations. We show that the Indian forecasts significantly affect farmer investment decisions, that the skill of the forecasts varies substantially across areas of India, and that farmers respond more strongly to the forecast where there is more forecast skill and not at all when there is no skill. Our profit-function estimates, using an IV strategy in which the monsoon forecast serves as the main instrument, indicate that Indian farmers on average under-invest. We also provide the first quantitative evidence that investment returns vary substantially by rainfall realizations. This sensitivity of returns to weather implies that an estimate of the returns to an investment at only one point in time may be a poor estimate of sub-optimal investment in risky environments.

We used our estimates to quantify how farmers' responses to forecasts affect both the level and variability in profits as the skill of forecasts increased. Increases in forecast skill would both increase average profit levels and decrease profit variability. We also showed that allowing farmers to better match their *ex ante* investments to *ex post* rainfall outcomes by improving forecast skill may outperform rainfall insurance contracts in terms of both the first and second moments of farm profits.

The possibility of improvements in forecasting weather realizations also has important consequences for the provision and design of agricultural insurance contracts. Given access to conventional weather index insurance products, which are sold at a fixed price up to the start of the farming season, farmers will adjust their demand for insurance in response to skilled forecasts, as has been suggested by Robertson *et al* (2010). Contrary to conventional belief, then, weather index insurance products can be subject to adverse selection, and the strength of that selection will increase as forecast accuracy increases. There are two ways to overcome this adverse selection: index insurance can be sold only before the release of skilled forecasts, or the price of the insurance must vary depending upon the forecast.

Even abstracting from the reality of basis risk, risk-averse farmers who make investments influenced by forecasts cannot achieve complete insurance and productive efficiency using weather index insurance alone. The responsiveness of inputs to forecasts implies that the loss that a farmer faces upon the realization of bad weather depends upon the prior forecast: the loss is greater if the forecast had been for good weather then if it had been for bad weather. To achieve full insurance, the farmer would require a larger payout in the event of a drought following a forecast of good weather than in the event of a drought following a forecast of a drought. This is a general point: if the production process is dynamic – decisions made over time contingent on the revelation of information about the probability of the realization of a random shock – then full insurance requires insurance that covers not just the final realization of that shock, but the entire sequence of decision-relevant signals.

There is thus a missing market for *forecast insurance*. As we have shown, access to skilled forecasts increases a farmer's expected profits and expected utility. It does, however, generate a new, particularly bad state of nature: a misleading forecast of good weather. Here, the losses of a farmer are particularly high because of the high investments that the erroneous forecast has induced. In the absence of conventional weather index insurance, there would be demand, in particular, for insurance against this specific event. An insurance product that paid out when bad weather followed a forecast of good would be a valuable financial innovation.

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Table 1
Descriptive Statistics: ICRISAT Panel (2005-2011) and REDS Panel (1999 and 2006)

Variable	Mean	Sd
ICRISAT Panel 2005-2011		
Kharif planting-stage investment (2005 rupees)	11949.7	13061.9
Annual profits (2005 rupees)	32700.8	61063.6
Total acres owned	8.68	7.44
Share irrigated acres	.497	.376
Share acreage with soil depth 1-3 feet	.647	.367
Share acreage with soil depth >3 feet	.244	.376
June-September rainfall (mm)	507.7	318.2
CV rainfall	.614	.205
Southern peninsula forecast (% of normal June-September rain)	96.4	2.77
Forecast skill (correlation, forecast and June-September rain)	.267	
Number of villages	6	
Number of farmers	477	
REDS Panel 1999 and 2006		
Kharif planting-stage investment (2005 rupees)	11315.9	97899.3
Total acres owned	5.27	7.33
Share irrigated acres	.637	.453
Share acreage with soil depth 1-3 feet	.392	.471
Share acreage with soil depth >3 feet	.268	.431
July-September rainfall (mm)	533.7	434.6
CV rainfall	.269	.125
Area-specific forecast (% of normal June-September rain)	98.1	2.70
Forecast skill (correlation, forecast and June-September rain)	.132	
Farmer cultivates rice	.510	.500
Number of villages	212	
Number of farmers	2219	

Table 2
Forecast Skill and Rainfall Characteristics, 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 correlation)	.451	.173	.193	.397	-.401	-.161

Map 1. Forecast Skill by Area (REDS 1999-2006)

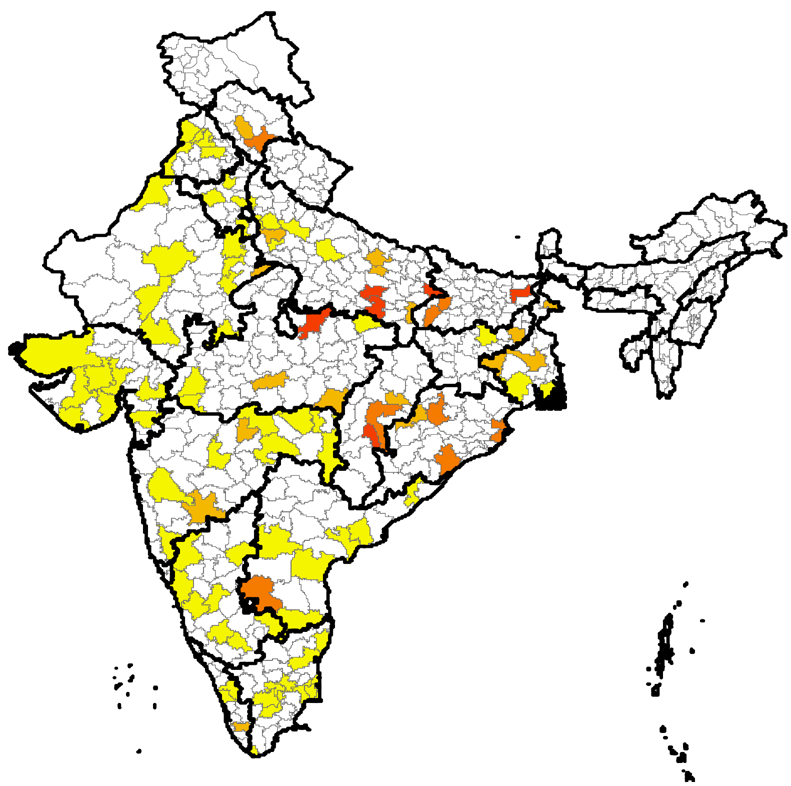


Table 3
Rainfall Forecasts and Log Planting-Stage Investments
(ICRISAT Panel, 2005-2011)

Sample	All Villages	Maharasthra (high skill)	Andhra Pradesh (no skill)	All Villages	Maharasthra (high skill)	Andhra Pradesh (no skill)
Forecast rain (*t*)	.0156	.0240	.00872	1.08	1.44	1.39
	(1.91)	(2.34)	(0.67)	(2.88)	(3.08)	(1.95)
Forecast rain squared (*t*)	-	-	-	-.00542	-.00717	-.00789
				(2.86)	(3.03)	(2.16)
Rain (*t*-1)	.000052	.000067	.000071	.000058	.000051	.00019
	(0.70)	(0.79)	(0.43)	(0.79)	(0.61)	(1.09)
Forecast rain (*t*-1)	.0100	.0132	.0127	.0105	.0138	6.76
	(1.14)	(1.21)	(0.88)	(1.20)	(1.27)	(1.67)
Rain (*t*-1) x soil depth, > 3	.00052	.00059	-	.00048	.00061	-
	(3.54)	(3.49)		(3.28)	(3.65)	
Rain (*t*-1) x soil depth, 1-3	.00007	.00002	.00027	.00010	.00002	.00028
	(0.65)	(0.15)	(1.31)	(0.88)	(0.14)	(1.29)
F(8, *n*) all forecast (*t*) and forecast interaction variables=0 [*p*]	-	-	-	2.12	3.50	1.04
				[.031]	[.0006]	[.409]
d log investment/*d*forecast (*t*) at mean values	-	-	-	.0269	.0474	.0253
				(2.09)	(3.61)	(0.96)
Includes forecast interacted with land characteristics	N	N	N	Y	Y	Y
N	1603	1125	478	1603	1125	478

Absolute values of asymptotic *t*-ratios in parentheses. Contemporaneous forecasts interacted with land size, irrigation share, and four soil types in columns 4-6.

Table 4
Household FE Estimates: Rainfall Forecasts, Forecast Skill and Log Planting-Stage Investments
(REDS Panel, 1999 and 2006)

Variable	(1)	(2)	(3)	(4)
Forecast rain	-.0670 (1.60)	-.122 (1.47)	-.159 (1.93)	-.177 (1.94)
Forecast rain x skill	.168 (2.53)	.482 (4.28)	.453 (4.61)	.568 (2.93)
Forecast rain*irrigated land share	-	.0839 (1.23)	.0375 (0.64)	.0378 (0.74)
Forecast rain*skill* irrigated land share	-	-.383 (3.55)	-.211 (2.81)	-.218 (1.79)
Forecast rain x rice area	-	-	-	-.00977 (0.09)
Forecast rain x skill x rice area	-	-	-	.00541 (0.05)
Forecast rain x rainfall CV	-	-	-	.000074 (0.49)
Forecast rain x skill x CV	-	-	-	-.00049 (1.88)
Includes all forecast and forecast/skill interactions	N	N	Y	Y
N	4438	4438	4438	4438

Absolute values of asymptotic *t*-ratios in parentheses clustered at the forecast area level. Skill is the correlation between July-September rainfall and the relevant area-specific forecast using the seven-year monthly rainfall times-series for each REDS village. The land characteristics include the four soil types, total land owned, irrigation share, and the two soil depth variables.

Table 5
Rainfall Forecasts, Forecast Skill and Log Planting-Stage Investments Using the Forecast Skill Measure with Village-Specific Intercepts, by Sample and Estimation Procedure
(REDS Panel, 1999 and 2006)

Sample	Full Sample	Districts with Skill	Districts with Skill
Estimation Method	Household FE	Household FE	Household FE, Corrected
Forecast rain	-.0674 (1.60)	-.0412 (1.80)	-.293 (4.98)
Forecast rain x skill	.00299 (3.27)	.00227 (4.55)	.0135 (4.99)
N	4438	1856	1856

Absolute values of asymptotic *t*-ratios in parentheses clustered at the forecast area level in columns one and two. Absolute values of bootstrapped *t*-ratios clustered at the forecast area level in column three. The specification for the district-specific forecast skill measure, β_j based on the village-specific seven-year times series of monthly rainfall, is: $R_{jk} = v_{jk} + \beta_j F_j + \varepsilon_{jk}$, where j=district and k = village. The reliability index used to correct for measurement error bias, based on the estimated district-specific standard errors of the forecast skill coefficients, is .688.

Table 6
Household FE-IV Profit Function Estimates: The Returns to Planting-Stage Investments
(ICRISAT Panel, 2005-2011)

Variable/specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	Profits	Profits	Profits	Profits	Profits	Profits, 10% Discount	Profits
Planting-stage investment	-2.64 (2.71)	-4.062 (2.00)	-1.22 (0.450	-1.18 (0.43)	.298 (0.08)	-.0878 (0.03)	-9.08 (1.38)
Planting-stage investment x rainfall	.00597 (3.71)	.0129 (3.62)	.0127 (2.86)	.0017 (0.43)	.0140 (2.69)	.0127 (2.73)	.00790 (1.21)
Planting-stage investment squared (x10^{-5})	-	2.14 (0.76)	.0823 (0.25)	6.81 (0.90)	-.588 (0.14)	-.126 (0.03)	16.9 (1.20)
Planting-stage investment squared x rainfall (x10^{-7})	-	-1.16 (2.27)	-1.19 (2.14)	-.926 (0.78)	-1.33 (2.16)	-1.22 (2.20)	-1.11 (1.20)
Total sick days adults	-	-	-	-	-	-	48.9 (0.06)
$\chi^2(2)$ test: investment, investment x rainfall=0 [*p*]	14.4 [.0008]	-	-	-	-	-	-
$\chi^2(2)$ test: investment, investment squared, investment x rainfall, investment squared x rainfall=0 [*p*]	-	19.0 [.0008]	19.7 [.0006]	2.80 [.592]	18.1 [.0012]	17.6 [.0015]	11.6 [.0210]
Village/year fixed effects	N	N	Y	Y	Y	Y	Y
Villages	All	All	All	Andhra	Maharashtra	Maharashtra	Maharashtra
N	1667	1667	1667	515	1152	1152	569

Absolute values of asymptotic *t*-ratios in parentheses. Specification also includes current-year annual and July-September rainfall, the monsoon onset date, the monsoon end date, prior-year rainfall, current-year and prior-year rainfall squared, and current-year rainfall and prior-year rainfall interacted with total landholdings, irrigated landholdings, soil depth, and four soil types. The instruments include the rainfall forecast, its square and the rainfall forecast interacted with the soil and landholding variables, annual and July-September rainfall, and the monsoon start date.

Table 7
Simulation Results: Effects of Providing Rainfall Insurance Compared with Increasing Forecast Skill, Holding Investment Fixed,
on Mean Rainfall and Rainfall Variability

Outcomes	Baseline: No rainfall insurance No forecast skill	Rainfall insurance No forecast skill 8% investment increase	No insurance Forecast skill = .45 No investment increase
Mean profits	15,780	16,248	16,796
Net profit variability (sd)	31,096	30,641	30,301

Figure 1. Local-IV Estimates of the Returns (dπ/dx) to Planting-Stage Investments, by Rainfall Realization (mm) and Specification

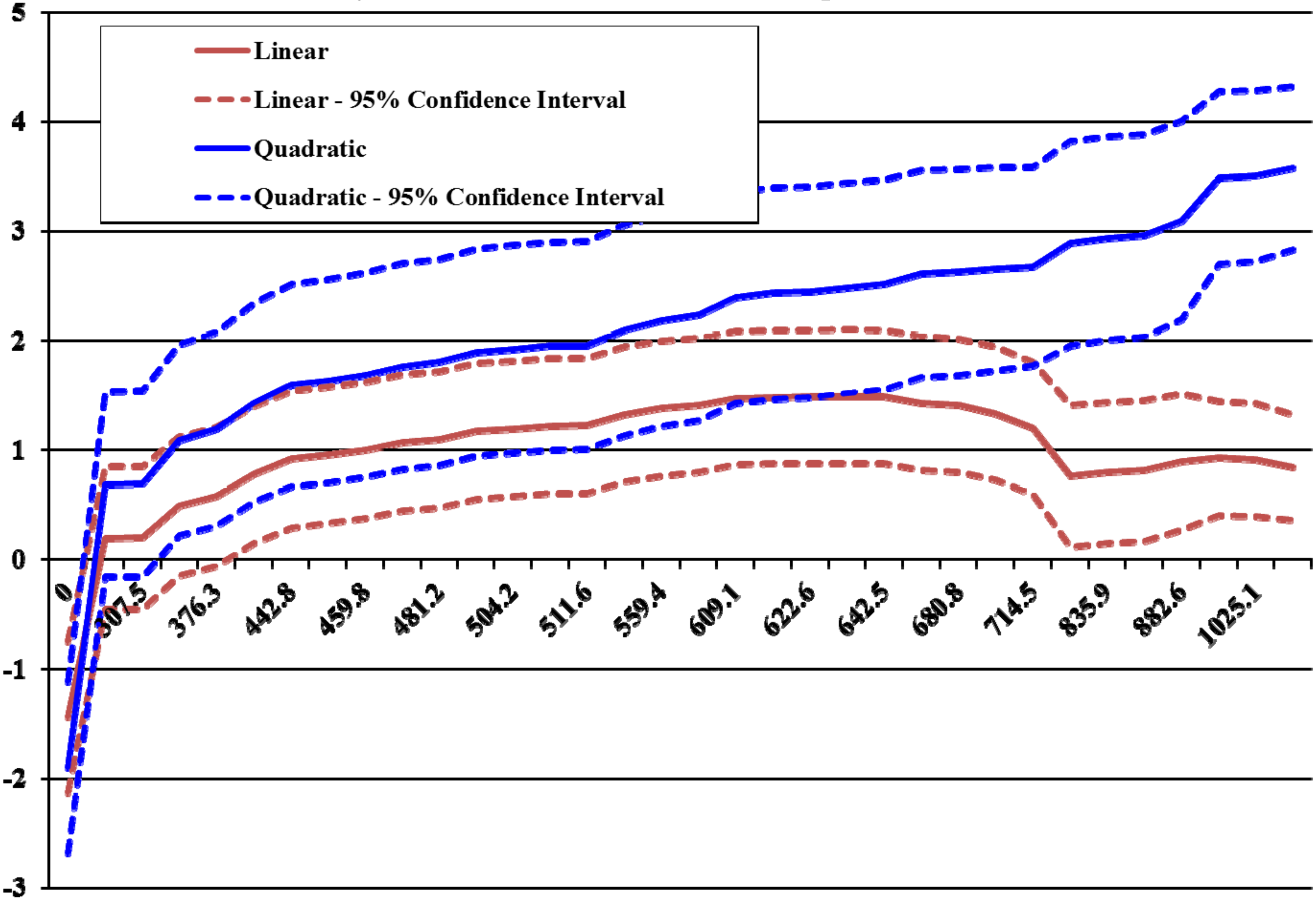


Figure 2
Relationship Between Crop-Year Farm Profits and *Kharif* Planting Investments (x10^{-3}),
by Realized *Kharif* Rainfall

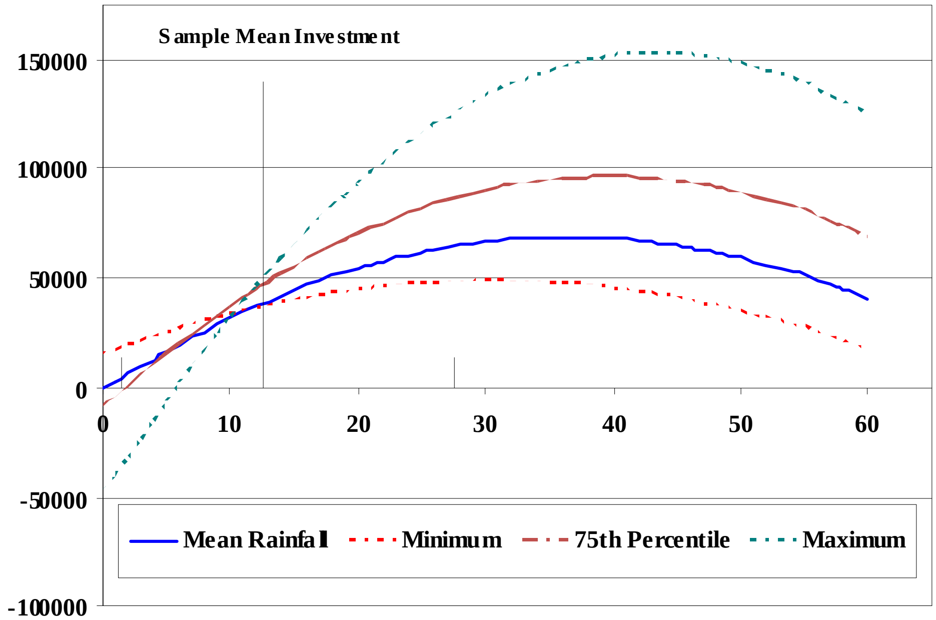
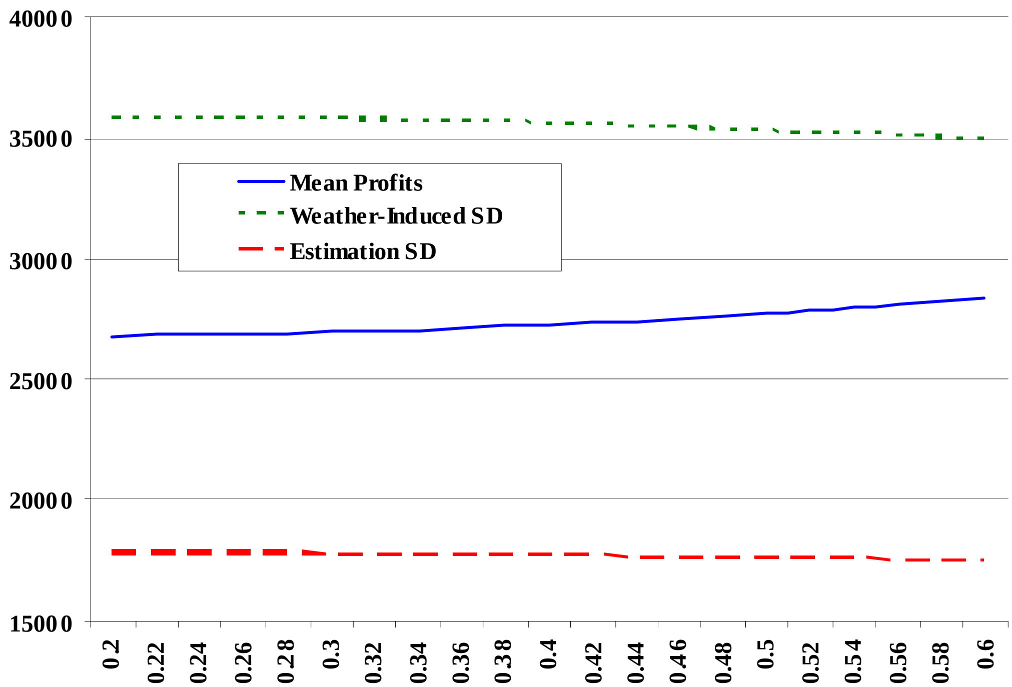


Figure 3. Mean Profits, Rainfall-Induced Profit Variability, and Estimation Error,
by Forecast Skill



Appendix for Online Publication: Propositions and Appendix Tables and Figures

Proposition 1: *A risk-averse farmer chooses lower levels of planting-season inputs then would a profit-maximizing farmer.*

Suppose the forecast is B. A profit-maximizing farmer would chose x_0 so that:

(A1) $$q\frac{\partial f_b}{\partial x_0} + (1-q)\frac{\partial f_g}{\partial x_0} = r.$$

The profit-maximizing farmer sets the expected marginal product of farm inputs equal to the rate of return on financial assets.

In contrast, a risk-averse farmer uses fewer inputs and keeps more of his resources in the risk free net savings. The first order conditions for the choice of x_0 and a, conditional on a forecast of B, are

(A2) $$-u'(c^0) + \beta\left(qu'(c_b^1)\frac{\partial f_b}{\partial x_0} + (1-q)u'(c_g^1)\frac{\partial f_g}{\partial x_0}\right) = 0$$

(A3) $$-u'(c^0) + \beta r\left(qu'(c_b^1) + (1-q)u'(c_g^1)\right) = 0.$$

Thus

(A4) $$\begin{aligned} r\left(qu'(c_b^1) + (1-q)u'(c_g^1)\right) &= qu'(c_b^1)\frac{\partial f_b}{\partial x_0} + (1-q)u'(c_g^1)\frac{\partial f_g}{\partial x_0} \\ &< qEu'(c^1)\frac{\partial f_b}{\partial x_0} + (1-q)\,\mathrm{E}\,u'(c^1)\frac{\partial f_g}{\partial x_0} \end{aligned}$$

where $Eu'(c^1) \equiv qu'(c_b^1) + (1-q)u'(c_g^1)$ and the inequality follows from the convexity of *u()* and the assumption that $\frac{\partial f_b}{\partial x_0} < \frac{\partial f_g}{\partial x_0}$. Hence the optimal choice of x_0 for a risk-averse farmer, conditional on a forecast of B satisfies

(A5) $$r < q\frac{\partial f_b}{\partial x_0} + (1-q)\frac{\partial f_g}{\partial x_0}.$$

Comparing (A1) and (A5), we see that the optimal input levels of a risk-averse farmer are less than profit-maximizing. We've shown this conditional on a forecast of the bad state, but an exactly analogous argument holds given a forecast of the good state. The intuition is parallel to that of Sandmo (1971).

Proposition 2: *Planting period inputs are larger and net savings smaller after a forecast of good rainfall compared to a forecast of bad rainfall.*

First order conditions (A2) and (A3) define optimal input use x_0 conditional on a forecast of Bad weather, when forecast skill is q, which we write as $x_0(q|B)$. Similarly, optimal net savings is $a(q|B)$. The implicit function formula implies

(A6) $$\frac{dx_0(q|B)}{dq} = \frac{-1}{\det}\bullet\left\{\begin{array}{l}\left[\beta r^2\left(qu''(c_b^1)+(1-q)u''(c_g^1)\right)+u''(c_0)\right]\beta\left[u'(c_b^1)\frac{\partial f_b}{\partial x_0}-u'(c_g^1)\frac{\partial f_g}{\partial x_0}\right] \\ -\left[\beta r\left(qu''(c_b^1)\frac{\partial f_b}{\partial x_0}+(1-q)u''(c_g^1)\frac{\partial f_g}{\partial x_0}\right)+u''(c_0)\right]\left[\beta r\left(u'(c_b^1)-u'(c_g^1)\right)\right]\end{array}\right\}<0.$$

det is the determinant of the Jacobian and is positive. The inequality follows because $u'(c_b^1)\frac{\partial f_b}{\partial x_0} - u'(c_g^1)\frac{\partial f_g}{\partial x_0} < 0$ (this follows from the concavity of $u(.)$, $f_g(x_0) > f_b(x_0)$ and $\frac{\partial f_g(x_0)}{\partial x_0} > \frac{\partial f_b(x_0)}{\partial x_0}$ for all x_0). As the forecast skill improves, input use in the case of a forecast of poor weather declines. A similar comparative static shows that $\frac{da(q|B)}{dq} > 0$:

$$\frac{da(q\mid B)}{dq}=\frac{-1}{\det}\bullet\left\{\begin{array}{l}\left[\beta\left(\begin{array}{l} qu'(c_b^1)\dfrac{\partial f_b^2}{\partial x_0^2}+qu''(c_b^1)\left(\dfrac{\partial f_b}{\partial x_0}\right)^2 \\ +(1-q)u'(c_g^1)\dfrac{\partial f_g^2}{\partial x_0^2}+(1-q)u''(c_g^1)\left(\dfrac{\partial f_g}{\partial x_0}\right)^2\end{array}\right)+u''(c_0)\right] \\ \bullet\beta r\left[u'(c_b^1)-u'(c_g^1)\right] \\ -\left[\beta r\left(qu''(c_b^1)\dfrac{\partial f_b}{\partial x_0}+(1-q)u''(c_g^1)\dfrac{\partial f_g}{\partial x_0}\right)+u''(c_0)\right] \\ \bullet\beta\left(u'(c_b^1)\dfrac{\partial f_b}{\partial x_0}-u'(c_g^1)\dfrac{\partial f_g}{\partial x_0}\right)\end{array}\right\}>0.$$ Since

prob(S=b|B)=prob(S=g|G)=q, (3) implies that

$$x_0((1-q)\mid G)\equiv x_0(q\mid B)$$
$$a((1-q)\mid G)\equiv a(q\mid B).$$

Therefore

(A7) $$\frac{dx_0(q\mid G)}{dq}>0$$

and

(A8) $$\frac{d(a(q\mid G)}{dq}<0$$

So as long as forecasts are informative (*q>0.5*), $x_0(q|G)>x_0(q|B)$ and $a(q|G)<a(q|B)$. Therefore, a forecast of good weather (as opposed to bad) increases investment in inputs and reduces investment in the safe asset.

Proposition 3: *The increase in investment with a forecast of good weather (compared to a forecast of bad weather) is larger as forecast skill improves.*

From (A6) and (A7), $\dfrac{d(x_0(q\mid G)}{dq}-\dfrac{d(x_0(q\mid B)}{dq}>0.$

Proposition 4: *If farmers have decreasing absolute risk aversion, then despite the smoothly-operating credit/savings market, input use is higher for farmers with higher initial assets Y. The response of input use to forecasts varies by initial assets.*

$$\frac{dx_0(q\,|\,B)}{dY} = -\frac{1}{\det}\left\{\begin{array}{l}(-u''(c^0)\left(\beta r^2\left[qu''(c_b^1)+(1-q)\,u''(c_g^1)\right]+u''(c^0)\right)\\ +(u''(c^0))\left(\beta r\left[qu''(c_b^1)\dfrac{\partial f_b}{\partial x_0}+(1-q)u''(c_g^1)\dfrac{\partial f_g}{\partial x_0}\right]+u''(c^0)\right)\end{array}\right\}$$

$$= \frac{-\beta ru''(c^0)}{\det}\left(\left[qu''(c_b^1)r+(1-q)\,u''(c_g^1)\,r\right]-\left[qu''(c_b^1)\frac{\partial f_b}{\partial x_0}+(1-q)u''(c_g^1)\frac{\partial f_g}{\partial x_0}\right]\right)$$

(A9)
$$= \frac{-\beta ru''(c^0)}{\det}\left(qu''(c_b^1)\left(r-\frac{\partial f_b}{\partial x_0}\right)+(1-q)u''(c_g^1)\left(r-\frac{\partial f_g}{\partial x_0}\right)\right)$$

$$> \frac{-\beta ru''(c^0)}{\det}\left(qu''(c_b^1)\left(r-\frac{\partial f_b}{\partial x_0}\right)+(1-q)u''(c_b^1)\left(r-\frac{\partial f_g}{\partial x_0}\right)\right)$$

$$= \frac{-\beta ru''(c^0)u''(c_b^1)}{\det}\left(q\left(r-\frac{\partial f_b}{\partial x_0}\right)+(1-q)\left(r-\frac{\partial f_g}{\partial x_0}\right)\right)$$

$$> 0$$

where the first inequality is a consequence of $r < \dfrac{\partial f_g}{\partial x_0}$ and decreasing absolute risk aversion (which implies $\left|u''(c_b^1)\right| > \left|u''(c_g^1)\right|$). The second inequality is a consequence of (A5). An exactly parallel argument shows that input use increases with *Y* in the context of a good forecast as well. The sign of $\dfrac{d(x_0(q\,|\,G)}{dY} - \dfrac{d(x_0(q\,|\,B)}{dY}$ is not determined in general, because it depends on the rate of decline of absolute risk aversion relative to the rate of decline of the marginal product of investment. However, in general the response of input use to forecasts will vary with initial assets *Y.* Sandmo relies on similar reasoning (1971, equation 14).

Proposition 5: *Suppose complete irrigation eliminates rainfall risk. Then as the skill of the forecast increases, the difference in the responsiveness of farmers with and without irrigation to a forecast of good weather increases.*

A farmer whose land is fully irrigated has a different production function, so output and marginal productivity does not depend on the realized state: $f_g^I(x_0) \equiv f_b^I(x_0)$. For such a farmer $x_0(q|G)=x_0(q|B)$, and the farmer does not respond at all to the forecast. As the skill of the forecast increases, the difference in the responsiveness of farmers with and without irrigation to a forecast of good weather increases (by Proposition 3 applied to the farmers without irrigation).

Proposition 6: *Farmers who live in riskier environments will invest less in inputs, respond differently to forecasts, and respond differently to the skill of forecasts.*

Consider a mean preserving spread in output. We model this by rewriting the production functions as $f_g(x_0) = \widetilde{f_g}(x_0) + \gamma,\ f_b(x_0) = \widetilde{f_b}(x_0) - \gamma$. If $\pi = \frac{1}{2}$, then an increase in γ is an MPS. Conditional on either a bad or a good forecast, investment in inputs declines as the riskiness of production increases. In the case of a forecast of bad weather:

(A10)
$$\frac{dx_0(B)}{d\gamma} = \frac{-1}{\det(\mathrm{B})}\left\{\begin{array}{l} \left(\beta^2 r^2\left[qu''(c_b^1)+(1-q)u''(c_g^1)\right]+u''(c_0)\right) \\ \bullet\left(-qu''(c_b^1)\dfrac{\partial f_b}{\partial x_0}+(1-q)u''(c_g^1)\dfrac{\partial f_g}{\partial x_0}\right) \\ -\left(\beta r\left[qu''(c_b^1)\dfrac{\partial f_b}{\partial x_0}+(1-q)u''(c_g^1)\dfrac{\partial f_g}{\partial x_0}\right]+u''(c_0)\right) \\ \bullet\left(\beta r\left(-qu''(c_b^1)+(1-q)u''(c_g^1)\right)\right) \end{array}\right\}$$
$$= \frac{-\beta u''(c_0)}{\det(\mathrm{B})}\left(-qu''(c_b^1)\left(\frac{\partial f_b}{\partial x_0}-r\right)+(1-q)u''(c_g^1)\left(\frac{\partial f_g}{\partial x_0}-r\right)\right) < 0.$$

The inequality follows because $\frac{\partial f_b(x_0)}{\partial x_0} < r < \frac{\partial f_g(x_0)}{\partial x_0}$. Analogous reasoning shows $\frac{\partial x_0(G)}{\partial \gamma} < 0$ as well. Farmers reallocate their investment from risky inputs to the safe asset as the riskiness of production rises. It will be important in our empirical work to be able to distinguish the effects of forecast skill (which increases investment) from the effects of riskiness, since the two may be inversely correlated across space. The interaction effects of the riskiness of production and the responsiveness of investment to a forecast of good weather will also in general be nonzero, although the sign of the interaction effect is ambiguous ($\frac{dx_0(G)}{d\gamma} - \frac{dx_0(B)}{d\gamma}$ cannot be signed). Similarly, the effect of an MPS in production on the response of investment to a change in forecast accuracy is generally nonzero, but of ambiguous sign.

Proposition 7: *Expected profits and expected utility increase with forecast skill.*

$$
\begin{aligned}
\frac{dE(profits)}{dq}\cdot 2 =& \left[f_g(x_0(q\,|\,G)) - f_b(x_0(q\,|\,G)) \right] + \left[f_b(x_0(q\,|\,\mathrm{B})) - f_g(x_0(q\,|\,\mathrm{B})) \right] \\
& + \frac{dx_0(q\,|\,G)}{dq}\left\{ q\left[\frac{\partial f_g(x_0(q\,|\,G))}{\partial x_0} - r \right] + (1-q)\left[\frac{\partial f_b(x_0(q\,|\,G))}{\partial x_0} - r \right] \right\} \\
& + \frac{dx_0(q\,|\,B)}{dq}\left\{ q\left[\frac{\partial f_b(x_0(q\,|\,B))}{\partial x_0} - r \right] + (1-q)\left[\frac{\partial f_g(x_0(q\,|\,B))}{\partial x_0} - r \right] \right\} \\
& > 0
\end{aligned}
$$

The first two terms sum to a positive because $x_0(q\,|\,G) > x_0(q\,|\,B)$. These are the direct effect of improved forecast skill on better matching input choices to the realized state; these terms would be the same for a risk neutral farmer who simply maximizes profit. The second two terms are the effect of improved forecast skill on reducing the risk faced by the farmer. They sum to a positive as well, because the reduced risk permits a risk-averse farmer to increase investment, on average, reducing the gap in the expected marginal product of investment in inputs and the return on the risk free asset summarized by (A5). The second two terms sum to a positive because $\frac{u'(c_b^1\,|\,\mathrm{G})}{u'(c_g^1\,|\,\mathrm{G})} > \frac{u'(c_b^1\,|\,\mathrm{B})}{u'(c_g^1\,|\,\mathrm{B})}$ (since $x_0(q\,|\,G) > x_0(q\,|\,B)$ and $a(q\,|\,B) > a(q\,|\,G)$). This in turn (by (A4)) implies that

$$
q\frac{\partial f_g(x_0(q\,|\,G))}{\partial x_0} + (1-q)\frac{\partial f_b(x_0(q\,|\,G))}{\partial x_0} > q\frac{\partial f_b(x_0(q\,|\,B))}{\partial x_0} + (1-q)\frac{\partial f_g(x_0(q\,|\,B))}{\partial x_0}.
$$

Now consider expected utility conditional on a forecast of good rainfall.

$$
\begin{aligned}
&\frac{dE(u\,|\,G)}{dq}=\beta\left[u(c_g^1(q\,|\,G))-u(c_b^1(q\,|\,G))\right]\\
&-u'(c^0)\cdot\left(\frac{dx_0(q\,|\,G)}{dq}+\frac{da(q\,|\,G)}{dq}\right)\\
&+\frac{da(q\,|\,G)}{dq}\beta r\left[qu'(c_g^1(q\,|\,G))+(1-q)u'(c_b^1(q\,|\,G))\right]\\
&+\frac{dx_0(q\,|\,G)}{dq}\beta\left[qu'(c_g^1(q\,|\,G))\frac{\partial f_g(x_0(q\,|\,G))}{\partial x_0}+(1-q)u'(c_b^1(q\,|\,G))\frac{\partial f_b(x_0(q\,|\,G))}{\partial x_0}\right]\\
&=\beta\left[u(c_g^1(q\,|\,G))-u(c_b^1(q\,|\,G))\right]\\
&-u'(c^0)\cdot\left(\frac{dx_0(q\,|\,G)}{dq}+\frac{da(q\,|\,G)}{dq}\right)\\
&+\left[\frac{dx_0(q\,|\,G)}{dq}+\frac{da(q\,|\,G)}{dq}\right]\beta r\left[qu'(c_g^1(q\,|\,G))+(1-q)u'(c_b^1(q\,|\,G))\right]\\
&=\beta\left[u(c_g^1(q\,|\,G))-u(c_b^1(q\,|\,G))\right].
\end{aligned}
$$

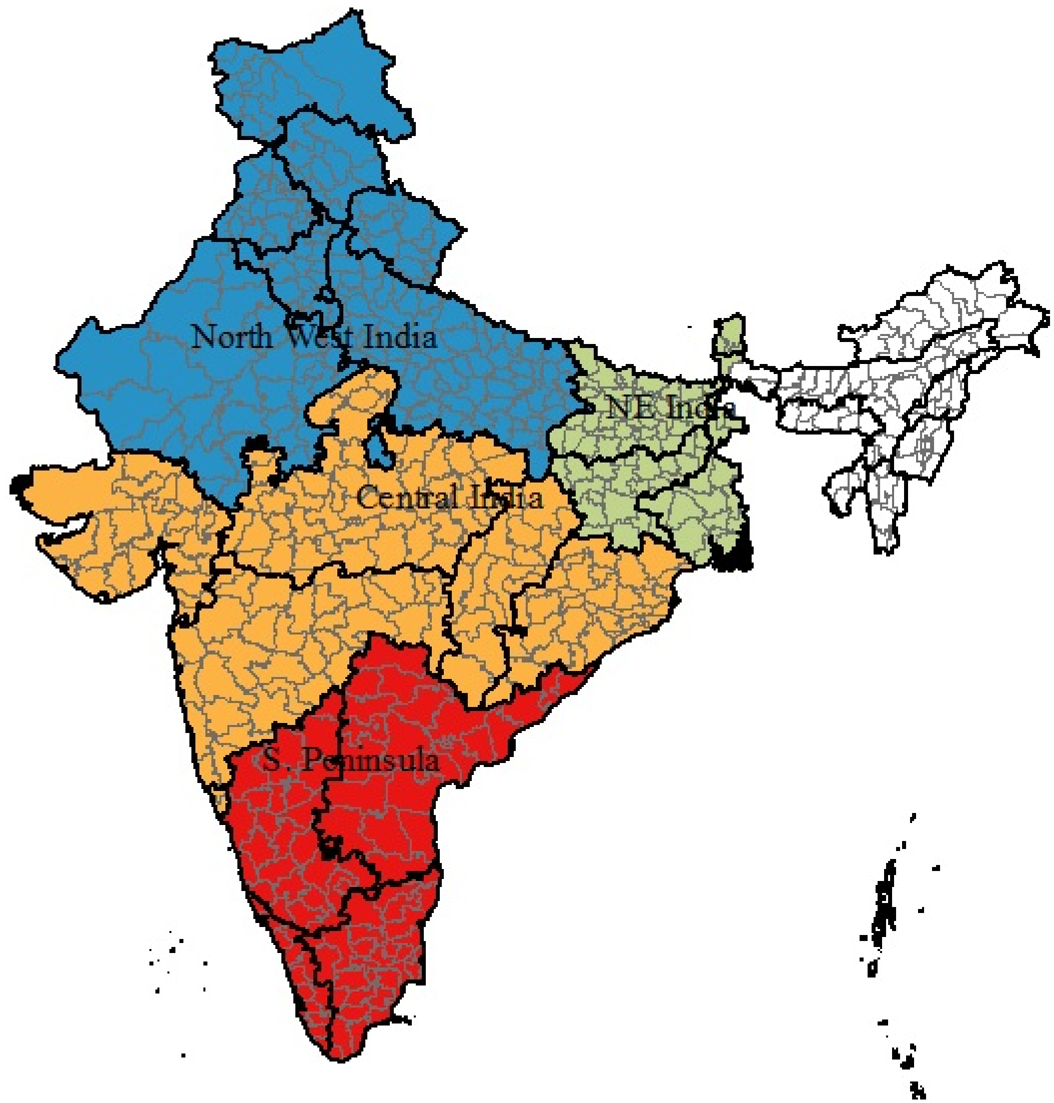
The second equality follows from the analogue of (A4) for the case of a forecast of Good weather, and the third equality follows from the analogue of (A3) for the case of a forecast of Good weather. Do the same exercise for expected utility conditional on a forecast of Bad weather, and sum weighted by ½ to find

(A11) $$\frac{dE(u)}{dq}\cdot 2=\beta\left[u(c_g^1(q\,|\,\mathrm{G}))-u(c_b^1(q\,|\,\mathrm{G}))+\left(u(c_b^1(q\,|\,\mathrm{B}))-u(c_g^1(q\,|\,\mathrm{B}))\right)\right]>0.$$

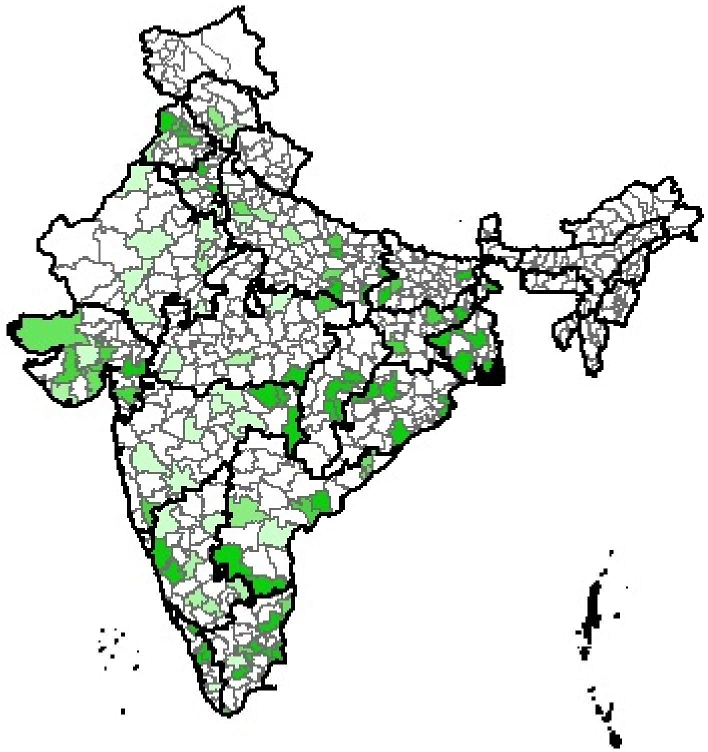
Expected utility rises because the gain in utility associated with the forecast being correct when the forecast is for good weather is larger than the loss in utility associated with the forecast be correct when the forecast is for bad weather (because *a* is higher and x_0 lower with B than with G).

Appendix Map A1

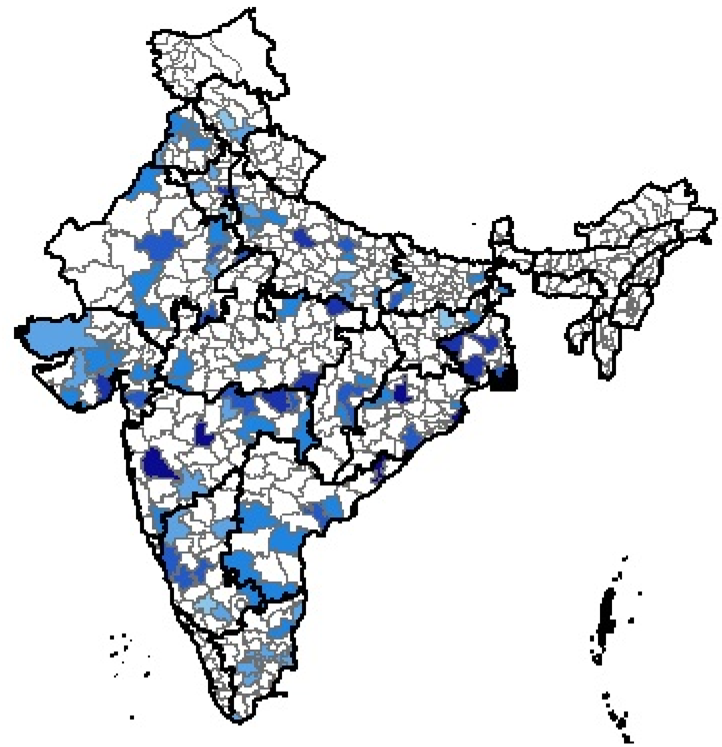
India Meteorological Department



Map A2. Rice-Growing Areas by District (REDS)



Map A3. Rainfall CV by District (REDS)



Appendix Table A1
Savings Accounts of ICRISAT Households and Annual Interest Rates,
Weighted by Account Value

Account	Interest Rate Mean	Interest Rate SD	Account Value (Rs)
Chit Funds	23.18	3.45	1,779,525
Co-operative Bank	5.97	1.33	1,297,245
LIC/PLI policies	8.14	2.17	3,117,557
National Bank	7.35	1.38	2,811,895
Others (GPF, etc.)	8.36	2.03	656,550
Post Office	8.40	2.33	492,600
Self Help Group	12.15	7.69	705,355
Total	10.44	6.49	10,878,727

Appendix Table A2
Rainfall Forecasts, Profits and Planting-Stage Investments
(ICRISAT Panel, 2005-2011)

Estimation method	Household FE	Household FE-IV		
Variable	Profits (*t*-1)	Log planting-stage investments (*t*)		
Sample	All Villages		Maharasthra (high skill)	Andhra Pradesh (no skill)
Forecast rain (*t*-1)	-303490 (2.68)	-	-	-
Forecast rain squared (*t*-1)	1534.4 (3.97)	-	-	-
Forecast rain (*t*)	32159 (0.46)	.572 (1.22)	1.37 (2.87)	-.419 (0.44)
Forecast rain squared (*t*)	-163.3 (0.68)	-.0048 (2.46)	-.0068 (2.78)	.00036 (0.07)
Profits (*t*-1) x 10^{-6}	-	.722 (0.79)	.106 (0.27)	6.76 (1.67)
Rain (*t*-1) x soil depth, > 3	-18.7 (1.37)	.00052 (3.25)	.00067 (3.76)	-
Rain (*t*-1) x soil depth, 1-3	34.0 (1.66)	.00015 (2.08)	.00051 (0.51)	.00033 (2.52)
$\chi^2(2)$ forecast (*t*) variables=0 [*p*]	0.30 [.739]	7.65 [.022]	9.63 [.008]	2.10 [.350]
$\chi^2(2)$ forecast (*t*-1) variables=0 [*p*]	8.47 [.000]	-	-	-
$\chi^2(8)$ all forecast (*t*) interaction variables=0 [*p*]	-	13.5 [.096]	15.6 [.016]	5.48 [.705]
d loginvestment/*d*forecast (*t*) at mean values	-	.480 (2.49)	.688 (2.85)	-.101 (0.22)
N	1399	1399	974	425

Absolute values of asymptotic *t*-ratios in parentheses. Lagged profit specification also includes lagged rainfall, lagged rainfall interacted with land size, irrigation share, and four soil types and the lagged and contemporaneous forecasts interacted with land size, irrigation share, and four soil types. The investment specification also includes the forecast interacted with land size, irrigation share, and four soil types.

Appendix Table A3
Household FE-IV Estimates: The Effect of Rainfall Forecasts on Planting-Stage Investments including the Monsoon Start Date
(ICRISAT Panel, 2005-2011)

Sample	All Villages	Maharasthra (high skill)	Andhra Pradesh (no skill)
Forecast rain (*t*)	.630	1.11	-.199
	(1.27)	(2.07)	(0.20)
Forecast rain squared (*t*)	-.0051	-.0054	-.00069
	(2.39)	(1.98)	(0.14)
Profits (*t*-1) x 10^{-6}	.653	.326	7.52
	(0.67)	(0.33)	(1.87)
Rain (*t*-1) x soil depth, > 3	.00052	.00068	-
	(3.29)	(3.80)	
Rain (*t*-1) x soil depth, 1-3	.00016	.00035	.00032
	(2.16)	(0.35)	(2.40)
Monsoon start date (x10^{-3})	-.122	.448	-1.82
	(0.34)	(1.08)	(2.40)
$\chi^2(2)$ forecast (*t*) variables=0 [*p*]	7.36	6.13	1.91
	[.025]	[.047]	[.384]
$\chi^2(8)$ all forecast (*t*) interaction variables=0 [*p*]	13.7	14.5	6.05
	[.090]	[.025]	[.641]
d log investment/*d*forecast (*t*) at mean values	.509	107.3	-19.0
	(2.43)	(2.07)	(0.22)
N	1399	974	425

Absolute values of asymptotic *t*-ratios in parentheses. Lagged profit specification also includes lagged rainfall, lagged rainfall interacted with land size, irrigation share, and four soil types and the lagged and contemporaneous forecasts interacted with land size, irrigation share, and four soil types. The investment specification also includes the forecast interacted with land size, irrigation share, and four soil types.

Appendix Table A4
FE Estimates of the Effect of Total Number of Adult Sick Days on On-Farm Family Labor in the *Kharif* Season
(ICRISAT Panel: 2005, 2006, 2010, 2011)

	All Villages	Maharasthra Villages
Total adult sick days	-.288	-.281
	(3.41)	(3.25)
N	1156	835

Absolute values of *t*-ratios in parentheses.

Appendix Table A5
Unconstrained and Constrained Cross-Sectional Estimates:
Rainfall Forecasts, Forecast Skill and Log Planting-Stage Investments,
(REDS Panel, 1999 and 2006)

Variable	Unconstrained	Constrained[a]
Forecast rain	.0908 (0.09)	-.0791 (0.22)
Forecast x forecast skill	.125 (4.00)	.160 (180.3)
Forecast skill	-13.4 (4.31)	-16.8
N	4438	4438

[a]The constraint is forecast skill = -100*forecast*forecast skill estimated using household fixed effects and reported in column 1 of Table 4.
Absolute values of asymptotic *t*-ratios in parentheses clustered at the forecast area level. Skill is the correlation between July-September rainfall and the relevant area-specific forecast using the seven-year monthly rainfall times-series for each REDS village. Specifications also include mean rainfall, the coefficient of variation of rainfall, whether or not the village is in a rice-growing region, five soil characteristics, total land owned, share of owned land irrigated, and all land characteristics interacted with the forecast.

Appendix Figures

Distributions of Planting Stage Investments

Figure 1
Distribution of Planting-Stage Investments, ICRISAT Panel 2005-11

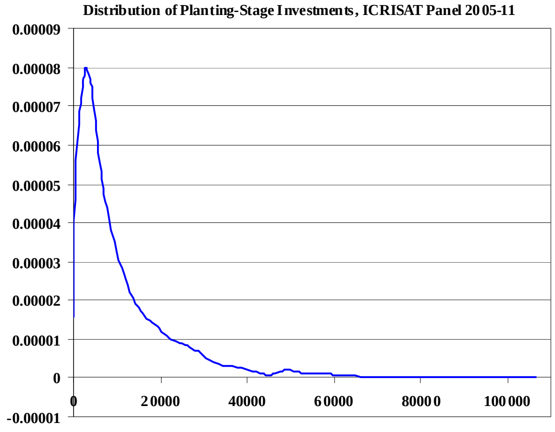
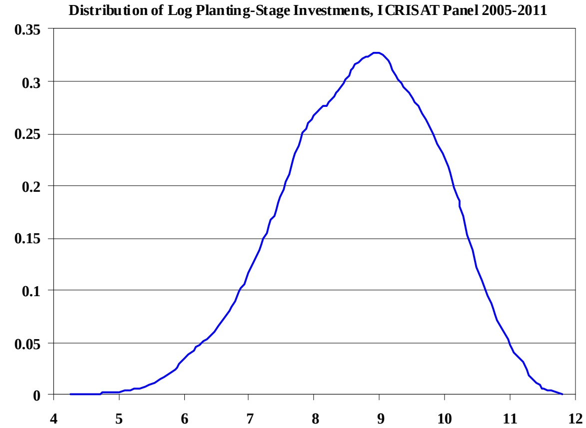


Figure 2
Distribution of Log Planting-Stage Investments, ICRISAT Panel 2005-2011



ICRISAT Panel, 2005-2011

REDS Panel, 1999 and 2006

Figure 3
Distribution of Planting-Stage Investments, REDS Panel 1999 and 2006

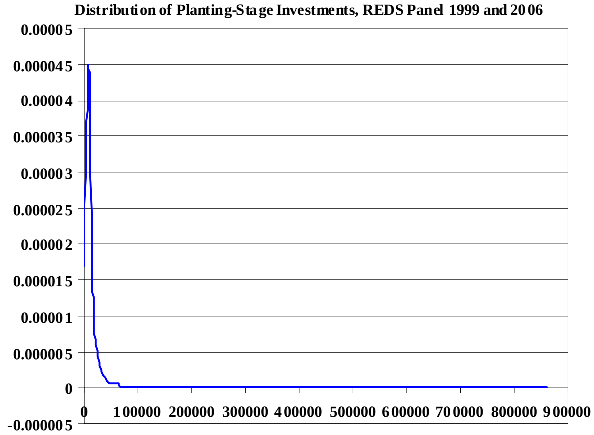


Figure 4
Distribution of Log Planting-Stage Investments, REDS Panel 1999 and 2006