DEPARTMENT OF ECONOMICS
YALE UNIVERSITY

P.O. Box 208268
New Haven, CT 06520-8268

http://www.econ.yale.edu/

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Forecasting Profitability

Mark Rosenzweig
Yale University

Christopher Udry
Yale University

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Abstract

We use newly-available Indian panel data to estimate how the returns to planting-stage investments vary by rainfall realizations. We show that the forecasts significantly affect farmer investment decisions and that these responses account for a substantial fraction of the inter-annual variability in planting-stage investments, that the skill of the forecasts varies 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. We show, using an IV strategy in which the Indian government forecast of monsoon rainfall serves as the main instrument, that the return to agricultural investment depends substantially on the conditions under which it is estimated. Using the full rainfall distribution and our profit function estimates, we find that Indian farmers on average under-invest, by a factor of three, when we compare actual levels of investments to the optimal investment level that maximizes expected profits. Farmers who use skilled forecasts have increased average profit levels but also have more variable profits compared with farmers without access to forecasts. Even modest improvements in forecast skill would substantially increase average profits.

Keywords: agriculture, forecasting, investment

JEL Codes: D24, D81, O12, O13, O14, Q12, Q54

"Everyone – from wheat farmers, to industrial conglomerates and motorcycle manufacturers – wants to glean any nugget of information they can about how the monsoon might pan out this year" (Staines, 2010)

1. Introduction

It is well-established that agricultural profits in developing countries depend strongly on weather realizations. It is similarly well-known from the development economics literature 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 directly improving farmers' capacity to deal with weather fluctuations by improving 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 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. 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)).

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.[1] 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.[2] Despite these sums devoted

[1] 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.

[2] For example, "Laxman Vishwanath Wadale, a 40-year-old farmer from Maharashtra's Jalna district, spent nearly 25,000 on fertilisers and seeds for his 60-acre plot after the Indian Meteorological Department (IMD) said in June that it stands by its earlier prediction of normal monsoon. Today, like lakhs of farmers, Wadale helplessly stares at parched fields and is furious with the weather office that got it wrong — once again. So far, rainfall has been 22%

to improvements in forecasting skill, we know of no estimate of the profitability of improving the accuracy of long-term forecasting.

We find that farmers in some regions of India appear to be responding to the IMD forecasts. Farmers surveyed in 2005-2011 as part of the "new" ICRISAT VDSA surveys exhibit substantial variability from year to year in their planting-stage investments. The mean (across farmers) coefficient of variation (over time) in land preparation and planting investments is 54 percent. This variation might be generated by lagged profits (if there are liquidity constraints), by lagged rainfall (which generates variation in investment in the following year through a "moisture overhang" effect), or by changes in input prices. We show, however, that a significant fraction of this variation is due to changing expectations about the profitability of planting-stage investments associated with the IMD forecast.

One metric for quantifying the impact of imperfect protection from risk, other market imperfections, or interventions designed to overcome such problems is the return on investments. In estimating these returns, economists have rarely (if ever) been able to take into account the variability in returns 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 (Duflo et al (2011), Banerjee and Duflo (2008), Banerjee et al (2013), Bloom et al (2012), de Mel et al (2008, 2009), Mobarak and Rosenzweig (2013), Karlan et al (2013), Fafchamps et al (2011), Udry and Anagol (2006)). This issue is most salient for agricultural production. Because of weather variability and other sources of aggregate risk, the standard errors associated with the estimated coefficients substantially overstate the precision of the return estimate. 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.[3] Studies spanning multiple localities over multiple years may be able to overcome this set of challenges.

In this paper, 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 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). 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 accept via these investments.

We first assess 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 (this correlation

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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).

[3] Most obviously, rainfall realizations will be correlated with the rainfall distribution, which typically will be related to agricultural returns (Duflo and Udry 2004).

is our measure of forecast skill). 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 ICRISAT respond strongly to the forecast where it has skill, in accord with the model. In particular, a ½ standard deviation increase in the monsoon forecast increases planting-stage investments by two-thirds. We exploit the variation across India in IMD forecast skill to show that farmers respond more strongly to the forecast the higher is the level of forecast 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.

Our IV estimates of the profit function indicate that the expected profit-maximizing level of investment is three times the observed mean investment by these farmers. ICRISAT farmers thus dramatically underinvest. Our profit function results also show that the returns to investment are extremely sensitive to rainfall realizations. This implies that inferences about the degree of underinvestment are heavily dependent rainfall. For example, if rainfall were at the mean of the observed rainfall distribution in the ICRISAT villages, a R10,000 increase in planting-stage investments (over a base of R12,000) would lead to an increase in profits of about R20,000 (over a base of R33,000). However, if rainfall were at the 75th percentile the same increase in planting-stage investments would yield R40,000 in additional profit, while at the minimum rainfall realization this additional investment would provide less than R10,000 in additional profit.

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. The simulations show that the gain to farmers of increased skill is similar to that found for farmers who obtain weather insurance, in that it is largest at extreme values – high or low – of rainfall. However, we show that farmers who exploit the forecast in making investment decisions experience greater profit variability due to the added risk of forecast failures. Based on 10,000,000 joint weather and forecast draws at each simulated skill level, we also show that expected farm profits are strongly increasing in skill. Each 0.1 increase in the correlation between the rainfall forecast and realization leads to an increase in profits of R43,000.

Finally, we use the simulations to explore how changes in the rainfall distribution predicted by climatologists as consequence of global warming (increased mean and variance of rainfall) affect the returns to increasing the skill of the monsoon forecast. The simulations under the global warming scenario indicate that while the mean and variance of profits rise, the high return to increasing forecast skill is little affected.

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 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.

Consider a farmer who makes decisions about farm inputs (*x*) in the planting period *0* and who realizes a harvest in period *1*. In the harvest period, there are two possible states, $S \in \{b, g\}$ with $prob(S = b) = \pi$. Output $f_s(x)$ depends on the input choice and the realized state, with $f_b(x) < f_g(x)$ and $\frac{\partial f_b(x)}{\partial x} < \frac{\partial f_g(x)}{\partial x}$ for all *x*. 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) $$c^0 = Y - x - a$$

(2) $$c_s^1 = f_s(x) + ra$$

Before making input decisions, 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 (Hamil and Juras, 2006).[4] Conditional on the receipt of forecast $F \in \{B, G\}$ the farmer's decision problem is

(3) $$\max_{x,a} u(c^0) + \text{prob}(S = b \mid \text{F}) u(c_b^1) + \text{prob}(S = g \mid \text{F}) u(c_g^1)$$

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

2.1 Forecasts and Input Decisions

In this subsection 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.

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

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

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

[4] 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.

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* and *a*, conditional on a forecast of B, are

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

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

Thus

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

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 $\frac{\partial f_b}{\partial x}<\frac{\partial f_g}{\partial x}$. Hence the optimal choice of x for a risk-averse farmer, conditional on a forecast of B satisfies

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

Comparing (4) and (8), 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.

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

Proof: First order conditions (5) and (6) define optimal input use *x* conditional on a forecast of Bad weather, when forecast skill is *q*, which we write as *x(q|B).* Similarly, optimal net savings is *a(q|B).* The implicit function formula implies

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

det is the determinant of the Jacobian and is positive. The inequality follows because $u'(c_b^1)\frac{\partial f_b}{\partial x}-u'(c_g^1)\frac{\partial f_g}{\partial x}<0$ (this follows from the concavity of *u(.),* $f_g(x)>f_b(x)$ and

$\frac{\partial f_g(x)}{\partial x} > \frac{\partial f_b(x)}{\partial x}$ for all *x*). As the forecast skill improves, input use in the case of a forecast of poor weather declines. A similar comparative static shows that $\frac{da(q\,|\,B)}{dq} > 0.$[5] Since *prob(S=b|B)=prob(S=g|G)=q*, (3) implies that

$$\begin{aligned} x((1-q)\,|\,G) &\equiv x(q\,|\,B) \\ a((1-q)\,|\,G) &\equiv a(q\,|\,B). \end{aligned}$$

Therefore

$$\frac{d(x(q\,|\,G)}{dq} > 0 \tag{10}$$

and

$$\frac{d(a(q\,|\,G)}{dq} < 0 \tag{11}$$

So as long as forecasts are informative (*q>0.5*), *x(q|G)>x(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.*

Proof: From (9) and (10), $\frac{d(x(q\,|\,G)}{dq} - \frac{d(x(q\,|\,B)}{dq} > 0.$

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[5] For the curious, $\frac{da(q\,|\,B)}{dq} = \frac{-1}{\det} \bullet \left\{ \begin{array}{l} \left[\beta \left(\begin{array}{l} qu'(c_b^1)\frac{\partial f_b^2}{\partial x^2} + qu''(c_b^1)\left(\frac{\partial f_b}{\partial x}\right)^2 \\ +(1-q)u'(c_g^1)\frac{\partial f_g^2}{\partial x^2} + (1-q)u''(c_g^1)\left(\frac{\partial f_g}{\partial x}\right)^2 \end{array} \right) + u''(c_0) \right] \\ \bullet \beta r\left[u'(c_b^1) - u'(c_g^1)\right] \\ -\left[\beta r\left(qu''(c_b^1)\frac{\partial f_b}{\partial x} + (1-q)u''(c_g^1)\frac{\partial f_g}{\partial x}\right) + u''(c_0)\right] \\ \bullet \beta\left(u'(c_b^1)\frac{\partial f_b}{\partial x} - u'(c_g^1)\frac{\partial f_g}{\partial x}\right) \end{array} \right\} > 0.$

2.2 Farmer Heterogeneity

Some dimensions of farmer heterogeneity are particularly salient for understanding how rainfall forecasts and their accuracy influence cultivation decisions. In particular, we show in this section that farmer wealth, the installed base of irrigation, and the riskiness of production all have direct effects on investment choices, and on the responsiveness of investment to forecasts.

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.*

Proof:

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

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

(12)
$$= \frac{-\beta r u''(c^0)}{\det}\left(qu''(c_b^1)\left(r-\frac{\partial f_b}{\partial x}\right)+(1-q)u''(c_g^1)\left(r-\frac{\partial f_g}{\partial x}\right)\right)$$

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

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

$$> 0$$

where the first inequality is a consequence of $r < \frac{\partial f_g}{\partial x}$ 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 (8). An exactly parallel argument shows that input use increases with *Y* in the context of a good forecast as well. The sign of $\frac{d(x(q\,|\,G)}{dY} - \frac{d(x(q\,|\,B)}{dY}$ 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.*

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.*

For a farmer whose land is fully irrigated, $f_g(x) \equiv f_b(x)$. Then *x(q|G)=x(q|B)*, and the farmer does not respond at all to the forecast. By proposition 3, 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.

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 $f_g(x) = \widetilde{f_g}(x) + \gamma,\ f_b(x) = \widetilde{f_b}(x) - \gamma$. If $\pi = \dfrac{1}{2}$, then an increase in γ is a 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:

(13)
$$\frac{dx(B)}{d\gamma} = \frac{-1}{\det(\mathrm{B})}\left\{\begin{array}{l} \left(\beta^2 r^2\left[qu''(c_b^1) + (1-q)u''(c_g^1)\right] + u''(c_0)\right) \\ \bullet\left(-qu''(c_b^1)\dfrac{\partial f_b}{\partial x} + (1-q)u''(c_g^1)\dfrac{\partial f_g}{\partial x}\right) \\ -\left(\beta r\left[qu''(c_b^1)\dfrac{\partial f_b}{\partial x} + (1-q)u''(c_g^1)\dfrac{\partial f_g}{\partial x}\right] + u''(c_0)\right) \\ \bullet\left(\beta r\left(-qu''(c_b^1) + (1-q)u''(c_g^1)\right)\right) \end{array}\right\}$$
$$= \frac{-\beta u''(c_0)}{\det(\mathrm{B})}\left(-qu''(c_b^1)\left(\frac{\partial f_b}{\partial x} - r\right) + (1-q)u''(c_g^1)\left(\frac{\partial f_g}{\partial x} - r\right)\right) < 0.$$

The inequality follows because $\dfrac{\partial f_b(x)}{\partial x} < r < \dfrac{\partial f_g(x)}{\partial x}$. Analogous reasoning shows $\dfrac{\partial x(G)}{\partial \gamma} < 0$ 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 ($\dfrac{dx(G)}{d\gamma} - \dfrac{dx(B)}{d\gamma}$ cannot be signed). Similarly, the effect of a MPS in production on the response of investment to a change in forecast accuracy is generally nonzero, but of ambiguous sign.

2.3 Welfare

In this subsection, we show that and that *ex ante* (before the forecast is made) both farmer profits and welfare increase with the skill of the forecast. To simplify the notation, we assume that the unconditional probability of bad weather (π) is ½.[6]

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

Proof:

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

The first two terms sum to a positive because $x(q\,|\,G) > x(q\,|\,B)$. 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 (8). 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 $x(q\,|\,G) > x(q\,|\,B)$ and $a(q\,|\,B) > a(q\,|\,G)$). This in turn (by (7)) implies that

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

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

---

[6] 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. In general,

$$
\frac{d\,\mathrm{Pr(Bad\ \ Forecast)}}{dq} = -\frac{2\pi - 1}{(2q-1)^2}\ .
$$

This is a consequence of our use of *q* to summarize forecast accuracy symmetrically for forecasts of good and bad weather. For $\pi \neq \frac{1}{2}$, there are additional terms in the comparative statics below which do not change the conclusions.

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

The second equality follows from the analogue of (7) for the case of a forecast of Good weather, and the third equality follows from the analogue of (6) 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

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

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* lower with B than with G).

3. Data

We use two panel data sets. The first is from the ICRISAT Village Dynamics in South Asia (VDSA) surveys from the years 2005-2011 describing farmer behavior in the six villages from the first generation ICRISAT VLS (1975-1984). The villages are located in the states of Maharashtra and Andhra Pradesh. There are two key features of these data for our purposes. First, there is a module providing daily rainfall for each of the six villages. This permits us to compute various time-specific measures of rainfall for estimating the sensitivity of investment returns to rainfall outcomes and for the assessment of forecast skill. Second, the data is collected at a high frequency so that accurate information is provided on the value of inputs by operation and by date. This enables us to measure *kharif*-season planting-stage investments that are informed by the IMD forecasts (which are issued at the end of June) but made prior to the full realization of rainfall shocks as well as the season-specific profits associated with those investments. These data thus enable us to estimate both the returns to planting-stage investments under different weather conditions and the response of those investments to the IMD forecasts. Our estimates of the profit function and planting-stage investment decisions use an unbalanced panel consisting of 477 farmers appearing in at least two survey years (1,667 observations).

The second panel data set we use is from the 1999 and 2007-8 Rural Economic and Development Surveys (REDS) carried out by the National Council of Economic Research (NCAER). This survey was carried out in 242 villages in the 17 major states of India. Like the ICRISAT survey, this survey elicited information on inputs by season and stage of production so that it is possible to also construct a measure of *kharif* planting-stage investments. The data set also includes monthly rainfall information by village for 212 villages covering the years 1999-2006. 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 taking into farmer fixed effects using these data.

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. 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. 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.

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 A shows the nominal annual interest rates of formal and informal savings accounts held by the ICRISAT households. 85% of the households have positive savings balances. The average nominal interest rate (weighted by value of deposit) is 10.4%. Average annual inflation over the span of the ICRISAT survey was 10.6%. Therefore, we set r=1 and do not discount output when we calculate profits.

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

Forecast skill may, however, vary by region. In the period 1999-2003, the forecasts were issued for three regions - Peninsular India, Northwest India and Northeast India. Starting in 2004, the forecasts have been issued for four broad regions of India (see Appendix Map A). To assess area-specific forecast skill, we obtained the correlations between the regional IMD forecasts and 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.

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

[7] 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).

5. Specification

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 an overhang effect of retained soil moisture. Hence we specify a linearized version of the farm profits of household *h* in village *v* in year *t* as

$$\begin{aligned} \pi_{hvt} &= \beta_x x_{hvt} + \beta_{xx} x_{hvt}^2 + R_{vt} \cdot \left[\beta_r + \beta_{rr} R_{vt} + \beta_{rx} x_{hvt} + \beta_{rxx} x_{hvt}^2 + \sum_k \left(\beta_{rk} Z_{khv} \right) \right] \\ &\quad + R_{vt-1} \cdot \left[\beta_{rl} + \beta_{rrl} R_{vt-1} + \sum_k \left(\beta_{rkl} Z_{khv} \right) \right] + \lambda_{\pi hv} + \varepsilon_{hvt}. \end{aligned} \tag{15}$$

x_{hvt} and x_{hvt}^2 are investments in planting period inputs (and its square) of household *h* in village *v* in year *t*, R_{vt} is the rainfall realization in that village in year *t*, and Z_{khv} are a set of fixed characteristics of the farm of household *h*, including total landholdings, irrigated landholdings, soil depth and four soil types. $\lambda_{\pi hv}$ is a household fixed effect that may be correlated with observed dimensions of household heterogeneity and ε_{hvt} is a shock to farm profits.

Excluded from (15) is the rainfall forecast (F_{vt}). This is the primary identification assumption of the empirical work. 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. The IMD long-range forecast is the prediction for the total amount of rainfall over the monsoon. Conditional on realized rainfall, the forecast of total rainfall in the monsoon effects profits only through its effect on x_{hvt}.[8] As shown in section 2, optimal input investment by household *h* depends upon this forecast (Proposition 2), the interaction of the forecast with the same set of fixed farm characteristics Z_{khv} (Propositions 5 and 6), lagged profits (Proposition 4), and forecast skill (itself interacted with the forecast itself, and with Z_{khv}) (Proposition 3).[9] In addition, x_{hvt} depends upon lagged rainfall realizations via soil moisture overhang,

[8] One concern is that conditional on our specific measures of realized rainfall (total annual rainfall, monsoon rainfall), the forecast of total rainfall is correlated with an unmeasured dimension of rainfall that matters for profits. It has been hypothesized (Binswanger and Rosenzweig 1993) that the monsoon onset date is a salient feature of rainfall for farm profits in India. However, in the ICRISAT data we see that conditional on even a subset of our measures of rainfall (monsoon rain, MR_{vt}), the forecast of total rainfall is not correlated with the onset date, measured in days from the start of the year: $\underset{(3.47)}{Onset_{vt} = 370} \; \underset{(7.47)}{-.139 MR_{vt}} \; \underset{(0.86)}{-1.064 F_{vt}}$. Absolute values of the asymptotic *t*-ratios in parentheses.

[9] Our model treats input prices as fixed. However, the forecast, which changes investment behavior of the population will likely affect planting-stage input prices. Our estimate of the effect of the forecast on investment

and this effect may vary across farmers depending on Z_{jhv} , most importantly soil depth (which effects the extent of moisture overhang). It is important that we control for lagged rainfall, 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, however, is not required for identification and is tested below). Planting stage input investments by household *h* in year *t* are therefore specified as

$$x_{hvt} = F_{vt} \cdot \left[\alpha_F + \alpha_{FF} F_{vt} + \sum_k \alpha_{kF} Z_{khv} \right] + \alpha_\pi \pi_{hvt-1}$$
$$+ R_{vt-1} \cdot \left[\alpha_r + \sum_j \alpha_{jr} Z_{jhv} \right] + F_{vt} \cdot q_v \cdot \left[\alpha_{qF} + \sum_k \alpha_{kq} Z_{khv} \right] + \lambda_{xhv} + \eta_{hvt}, \tag{16}$$

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.

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

In this section we present fixed-effects (FE at the farmer level) and fixed-effects instrumental variable (FE-IV) estimates of the profit function (15) that is quadratic in planting-stage investments using the ICRISAT panel data to assess the sensitivity of the returns to those investments to rainfall variability, exploiting the multiple years of the ICRISAT panel and its detailed information on inputs, outputs, and rainfall. As described in section 5, we use the IMD forecast, interacted with the characteristics of the farm and farmer, as instruments to predict planting-stage investments. All profit function specifications include current-year and prior-year annual and July-September rainfall, the squares of the rainfall variables, and the rainfall variables interacted with total landholdings, irrigated landholdings, soil depth, and four soil types (red, black, sandy, loam).

The first column of Table 3 reports FE estimates of the returns to planting-stage investments ignoring the possibility that the effects of planting-stage investments on profits depend on rainfall realizations and that the investments may be correlated with profit shocks. These estimates indicate that there are diminishing returns to planting-stage investments, with the two investment coefficients jointly significant. The second column reports the FE-IV estimates for the same specification. Both investment coefficients are individually statistically significant and considerably larger in absolute value than their FE counterparts. The point estimates indicate that the profit-maximizing farmer would invest 75,278 rupees at the planting stage. This compares with the average investment, as seen in Table 1, of 12,000 rupees. These estimates, which take into account the endogeneity of investment but not the dependence of investment returns on weather, thus suggest considerable under-investment.

If investment returns are sensitive to rainfall outcomes, then the second-column estimates of the “average” returns to investments and the inferred amount of under-investment would be incorrect, given diminishing returns. In the next two columns we report FE and FE-IV estimates, respectively, of the

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thus incorporates this equilibrium effect. There is a potential identification issue if the planting-stage input-price change has an intertemporal effect on harvest-stage labor supply. We think that this kind of intertemporal substitution has only second-order effects.

fully-specified profit function (15) in which the effects of the planting-stage investments depend on rainfall. For either estimation procedure we can strongly reject the hypothesis that the returns do not depend on rainfall. And for either we cannot reject the hypothesis that the returns vanish at zero rainfall - planting-stage investments thus wholly depend on rainfall outcomes. These estimates imply that *ex-post* optimal investments depend on realized rainfall outcomes, or, put differently, how much underinvestment one would infer from estimates depends on what is assumed to be the typical rainfall outcome.[10]

Figure 5 plots the relationship between profits and investments for rainfall at the mean and at the minimum, maximum and 75th percentile of the actual rainfall distribution in the ICRISAT villages based on the statistically-preferred FE-IV estimates. We take note of three important features of this.

First, the profit-maximizing amount of planting-stage investments increases with the level of rainfall. This feature demonstrates that information about the impending rains would induce a profit-maximizing farmer to change investments: for example, a farmer who knew that rainfall this year would be at the maximum of the ICRISAT observed distribution would invest fifty percent more than a farmer who knew that rainfall would be at the minimum of the distribution. This feature of Figure 5 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 optimal planting practice just from rainfall heterogeneity. For example, the profit-maximizing investment level is one-third higher at a rainfall mean corresponding to the 75th percentile of the ICRISAT than that for an area with a mean rainfall corresponding to the minimum of the ICRISAT rainfall distribution.

A second feature of the figure is that actual farmer investments are considerably lower than those that would maximize expected profits, consistent with Proposition 1. In this figure, we can see that the actual mean investment level observed in the sample is lower than the investment level that maximizes profit at the minimum rainfall level, which in turn is lower than the investment that maximizes expected profits. We calculate the expected profit-maximizing investment level in section 8.

Third, an estimate in one place at one time of the returns to investments 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 - the returns to a given investment vary 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 year of rainfall at the minimum of the distribution.

[10] Our instruments have power. The F(9, 1724)-statistics for the set of identifying variables including the forecast, the forecast squared, the forecast interacted with total landholding, the forecast interacted with irrigated landholdings, and the forecast interacted with July-September rainfall and annual rainfall and 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 full set of first-stage estimates are available upon request from the authors.

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.

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

The profit function estimates indicate that investment returns depend significantly on weather realizations. Thus, as our model shows, farmers benefit from rainfall forecasts and their planting-stage investments will be affected by such forecasts to the extent the forecasts have skill. But do changes in forecasts substantially alter investments? Table 4 reports estimates from the ICRISAT panel data of the planting-stage investment equation (16) in which the household's beginning-period endowment and the rainfall forecast affect planting investments. In that specification we treat lagged profits, reflecting the household's time-varying endowment at the start of the period, as endogenous, using the lagged IMD forecast and its square and the interactions of the lagged forecast with the farm land characteristics as instruments. The first column of the table reports the farmer fixed-effect (FE) estimates of the first-stage reduced-form equation for lagged profits. The lagged forecast coefficients in that equation are jointly statistically significant, indicating that the forecast is influencing farmer decisions, consistent with the first-stage estimates in the profit function estimation. Reassuringly, however, the contemporaneous forecast, announced after prior-period profits are realized, has no power in the lagged profit equation.

Column two reports the fixed effect-instrumental variables (FE-IV) estimates of the log planting-stage investment equation including predicted lagged profits. The IMD rainfall forecast significantly affects investment levels, as in Proposition 2. The forecast and forecast squared coefficients are jointly significant, as is the complete set of forecast interactions with land characteristics, which are not shown in the table (irrigation share, total acreage owned and four soil types). In accord with the model, a forecast of higher rainfall increases investments and the marginal effect, given at the bottom of the column, is also statistically significant and large. The point estimates, computed at the mean values of the interaction variables, indicate that a positive one percentage point increase in the forecasted rainfall deviation increases planting-stage investment by 48%. Lagged profits, however, do not have a statistically significant effect on investments made in the planting stage.

One concern is that the planting-stage investments, made after the onset of monsoon rains, also 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). This variable 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 at the .04 level.

Another concern is that the relationship between the forecast and investments in spurious. 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, the finding that planting-stage investments are 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. We estimated the planting-stage equation separately for the two sets of villages. The estimates of the planting-stage investment equation for the Maharashtra and Andhra villages are reported in columns three and four of Table 4, respectively. In accord with the model, the forecast variables indeed have no power in predicting investments in the Andhra Pradesh villages and the quantitative effect of variation in the forecast on investments is small and statistically insignificant. In contrast, the forecast variable coefficients are highly significant predictors of planting-stage investments for the Maharashtra farmers, with the point estimates indicating that forecast variation has a strong effect on those investments.

In the Maharashtra villages, there is no evidence that lagged profits are associated with investments, while this effect is marginally statistically significant in the Andhra Pradesh villages. The moisture overhang effect of lagged rainfall is an important and statistically significant determinant of investment in both states. In Maharashtra it is apparent at soil depths greater than 3 feet. Such deep soil is not observed in Andhra Pradesh; there the moisture overhang effect is significant for soils of 1-3 foot depth.[11]

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 other than differences in forecast skill. The REDS data, from which we have many more village-level estimates of forecast skill and many more farmers, allows 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 (16) excluding lagged profits (which did not seem to matter), given we only have two observations per farmer, but including the interactions between forecast and forecast skill and the interactions of forecast skill with other characteristics of the region and farmer. [12]

Column 1 of Table 5 reports FE estimates of the effects of the IMD forecast and the forecast interacted with forecast skill on the log of planting-stage investments for the 2219 farmers in the REDS data.[13] Consistent with the model, the profit function estimates, 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

[11] The net effect of higher responsiveness of investment to forecasts in Maharashtra and higher responsiveness to lagged profits in Andhra Pradesh 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, $p=0.027$).

[12] Excluding lagged profits from the specification does not significantly affect the forecast or other coefficients shown in Table 4.

[13]The set of interactions between the forecast and the characteristics of the individual farm were not statistically significant and are omitted.

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 5, 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) among unirrigated farmers a one percentage point increase in the forecast deviation increases planting-stage investments by 9%.

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. Map 2 shows the rice-producing areas in India, based on the cropping patterns of the farmers in the REDS. As can be seen 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. To assess if our finding of the higher responsiveness of investments to the 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). The fourth column of Table 5 displays these estimates, and Map 3 shows the geography of rainfall variability. As can be seen, neither the set of rice nor the set of CV interaction coefficients is statistically significant, while the magnitudes and statistical significance of the coefficients associated with the responsiveness of investments to forecast skill for irrigated and unirrigated farmers are unaffected.[14]

8. Optimal Input Choices and Forecasting

In this section we (a) obtain the profit-maximizing level of planting stage investment and (b) assess the contribution of the forecast to actual investment variability and average profit levels and profit variability.[15] We use simulations based on our estimates and the actual rainfall distribution characterizing the ICRISAT sample. The planting-stage investment choices of a risk-neutral (or fully-insured) farmer without access to forecasts would set the expected marginal return of these investments equal to the real discount factor. The expectation would be taken over the unconditional distribution of rainfall realizations, and we have hypothesized that the real discount factor is approximately 1 (a real interest rate of 0). We calculate the profit-maximizing planting-stage investment

[14] 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.

[15] In making this calculation, we are assuming that farmers are knowledgeable of the distribution of rainfall. Giné *et al.* (2009) show that for farmers in the semi-arid tropics of India, where the ICRISAT villages are located, at the .05 percent level one cannot reject that the perceived distribution of the rainfall onset date and the actual distribution were identical for 85% of farmers.

of a farmer by attributing to that farmer the mean characteristics of farmers in the Shirapur village sample, and then simulate profits at alternative levels of investment using the coefficients of our estimated profit function (Table 3, column 4) and repeated draws from the joint distribution of annual and monsoon rainfall in Shirapur. For each investment level, we calculate average profits over the 10,000,000 draws from the rainfall distribution. We then find the investment level that maximizes the expected value of profits. We begin with the actual means and correlations of the joint distribution of total rainfall, monsoon rainfall and the IMD rainfall forecast that we take from the data describing the village of Shirapur over the period 2005-2011.[16] In each simulation of profits we draw a total rainfall realization and a monsoon rainfall realization from the joint normal distribution defined by the covariance matrix defined by these parameters.[17] We find the profit-maximizing investment level to be R42,000, compared with actual mean investment in the ICRISAT sample of R12,000. As we noted in section 6, there is substantial underinvestment in planting-stage inputs, by a factor of more than 3.

We now compare this profit-maximizing investment level to the behavior of a typical farmer in the sample of Maharashtra farmers, who as we have seen in Table 4 respond to IMD forecasts, which vary from year to year. In Figure 6, we display the Maharashtra sample mean investments and estimated profit-maximizing investment level of a farmer with mean Shirapur sample characteristics. We also simulate the effect rainfall forecasts on the investments of a farmer. To isolate the responsiveness of planting-stage investment to variations in the forecast, we again assign to a farmer the mean characteristics of farmers in the ICRISAT sample, and also fix lagged profits at their mean, and lagged rainfall at its mean. We expose this farmer to the forecasts from a sequence of 20 draws from the joint distribution of annual rainfall, monsoon rainfall and the IMD forecast. We specify the skill of the forecast as $\rho = 0.43$, our estimate of forecast skill in Shirapur (from which we take the rainfall distribtution), and use the estimates of the investment coefficients in equation (16) from Column 3 of Table 4.

The line labeled "Responsive to Forecast" reports the farmer's adjustment of planting-stage investment in response to the forecast. We have eliminated variation in investment due to lagged profits (which is small and statistically insignificant in any case, as seen from the estimates reported in Table 4 column 3) and any variation due to the soil moisture overhang effect (which is an important source of variation in our sample, as can be seen in the same set of estimates). This is just an example of one particular sequence of 20 seasons of realizations of rainfall and forecasts; a different sequence would of course yield a different time path. Nevertheless, it is apparent from Figure 6 that planting-

[16] The rainfall forecast does *not* enter the present calculation of expected profits at each level of planting-season investment. But the rainfall forecast does, of course, affect the choice of planting-season investment described in the next paragraph, so we describe the joint distribution here. The covariance matrix for total rainfall (mm), monsoon rainfall (mm) and the IMD forecast (% of normal) is $\begin{pmatrix} 453.7 & 84861 & 348 \\ 84861 & 360.9 & 329 \\ 348 & 329 & 96.4 \end{pmatrix}$. As the simulations change the correlation between monsoon rainfall and the IMD forecast, we assume that the correlation between the total rainfall and the forecast changes proportionally, while of course the correlation between total and monsoon rainfall is fixed.

[17] We carried out Shapiro-Wilk and Shapiro-Francia tests for normality of the rainfall distribution covering a 23-year period for the village. Neither test indicated rejection of the null hypothesis at conventional levels of significance (p=.262, .699, respectively).

stage investments respond to the long-range monsoon forecast. Investment rises from the mean of R10,300 to nearly R13,000 in years when the forecast is for good rainfall, and falls to under R6,000 in the year of the simulation in which rainfall is predicted to be very low. The variation in investment attributable solely to forecast variation in the Maharashtra villages is sizable: the coefficient of variation of investment in this simulation is 15 percent, compared to an average c.v. of investment in these villages in our sample of 60 percent. So about ¼ of the variation in early-season investment in the villages is accounted for solely by variation in the rainfall forecast.

In figure 7 we display the estimated profits realized from this same sequence of draws of rainfall and forecasts. The "Sample Average" line is the profits achieved under each of the draws of the simulation of a farmer investing each year a fixed amount of R10,300. Given this sequence of rainfall realizations, this generates average profits of R42,300 with only a small amount of variability due to rainfall (because, as can be seen in Figure 5, at this low level of investment the rainfall variation leads to only mild variation in profits). In contrast, profits are extremely variable at the much higher profit-maximizing investment of R42,000. As expected this very large, profit-maximizing investment level also leads to much higher average profits: the mean profit over these 20 rainfall realizations is R86,000. The line labeled "Responsive to Forecast" shows profits under the scenario in which the farmer's investment adjusts to the forecast, as in Figure 6. By responding to forecasts, the farmer increases his mean profits to R46,625 over the "Sample Average" scenario mean of R42,300, while his mean investment increased only to R11,113 (from R10,300). As can be seen, this increased average profit comes at the cost of much more profit variability. There are two sources of risk that generate this increased variability: rainfall risk itself, and the risk that the forecast is incorrect. The worst outcome for the farmer now occurs in a year in which the forecast is for good weather (leading the farmer to increase early-season investment) but the actual realization of rainfall is poor. The fact that we find that farmers choose to adjust their inputs so strongly in response to imperfect forecasts, despite the much higher variability of profits generated by this decision, is indicative that farmers in the ICRISAT villages have access to some *ex post* risk sharing mechanisms (Townsend 1994; Mazzocco and Saini 2012), as well as of some form of borrowing friction that makes achieving the high "Profit-Maximizing" level of investment costly.

9. The Profitability of Changing Forecasting Skill

9.1 Returns under current weather conditions

Both datasets provide evidence that farmers adapt to the skill of IMD forecasts: in regions 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 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 assumptions regarding 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 (including its mean), 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.

These realizations, along with the mean values of farm characteristics in Shirapur (Z_{hv}) and the parameter estimates of the coefficients in equations (15) and (16) are used to generate a prediction of planting-stage investment, and (using the predicted planting-stage investment) farm profit. The parameter values for the coefficients in equation (16) are those from column 2 of Table 4, while $\hat{\alpha}_q$ and $\hat{\alpha}_{kq}$, which characterize the responsiveness of input choices to forecast skill, come from column 2 of Table 5. The parameter values for the coefficients in equation (15) are those from column 4 of Table 3. For each value of forecast skill, we again draw 10,000,000 realizations of rainfall and the forecast in order to characterize the distribution of profits.

The solid line in Figure 8 provides these initial results. It represents the mean of the distribution of profits for a typical Shirapur farmer, given the distribution of rainfall in Shirapur, at various levels of forecast skill. The key result is that increases in forecast skill have a very large effect on mean profits. As skill increases, the typical farmer responds more aggressively to match his planting-stage investment to the forecast, and that forecast more often is close to the rainfall realization, and therefore the profitability of farming is on average much higher. Increasing the correlation of the forecast with rainfall realizations by 0.1 causes an increase in profits of approximately R43,000 (over of a baseline profit of approximately R32,000).

The dashed line in Figure 8 shows that most of this gain to improved skill comes from farmers' increasing willingness, as forecaster skill increases, to adjust their input choices in response to the forecast. That line reports the results of simulations in which $\hat{\alpha}_q$ and $\hat{\alpha}_{kq}$ are set equal to zero, so that the responsiveness of farmers to the forecast is set at the mean responsiveness reported in column 2 of Table 4. In this case, an increase of 0.1 in forecaster skill is associated with only about R250 of additional profits.

Figure 9 emphasizes the scale of the weather risk faced by farmers. The curves labeled "Low" and "High" represent the 25th and 75th percentiles of the profit distribution, for each level of forecasting skill. Fully half of the profit realizations, then, fall even further from the mean than these curves. This variation dwarfs even the very large improvements in profits associated with a 0.1 increase in forecast skill. These simulated profits reflect only the consequences of village level rainfall shocks and the variance of the forecast itself, not any of the idiosyncratic variation in inputs or profits represented by the errors ε_{hvt} and η_{hvt} . Any single cross-section within a village or forecast region only provides information on profits conditional on this particular draw from the *{rainfall, forecast}* distribution.

Improvements in forecast skill have differential effects over the rainfall distribution. Figure 10 shows that improvements in the accuracy of rainfall forecasts are particularly valuable when rainfall is very low, and when it is very high. The mean of the rainfall distribution is approximately 430, so the smallest effect of increased skill is found in moderately good years of rain. The impact of increased forecast skill, therefore, replicates the *ex post* impact on net agricultural income (farm profit, inclusive of insurance premia and payouts) of crop or rainfall index insurance. Mobarak and Rosenzweig (2012), Cai et al (2010), Cole et al (2011) and Karlan et al. (2013) show that farmers with access to insurance organize production to take on more risk, so their net income increases in good rainfall states, and the insurance payouts make net income increase as well in poor rainfall states.

9.2 The Effects of Global Warming

How will global warming affect the returns to improving forecasting skill? In Figure 11, we present the results of simulations of rainfall under global warming based on parameters from the dominant Global Coupled Models linking monsoon behavior to global warming (Turner and Annamalai, 2012).[18] Changing the parameters of the rainfall distribution to match these predictions and replicating the simulation exercise yields the results summarized by the curve labeled "Warming optimal response". Profits on average increase at all skill levels, reflecting the higher mean rainfall predicted for the global warming scenario.[19] The high return to increasing forecast skill is little affected by global warming.

10. Conclusion

It is well-known that returns to investments depend on the realizations of stochastic outcomes, particularly for agriculture in which production takes place over time and output is sensitive to rainfall shocks. However, we know of no empirical studies that quantify the dependence of investment returns on rainfall or other aggregate *ex post* shocks. It is not possible to infer the degree of under-investment, an important indicator of market incompleteness, without knowledge of the distribution of stochastic shocks and their consequence for returns. This is because the optimal investment for a risk-neutral agent maximizes the expected value of profits over the full distribution of shocks. Thus an estimate of investment returns at one point in time may be a very poor estimate of sub-optimal investment in risky settings. The existence of agricultural risk also implies that farmers would benefit from improved signals of future rainfall realizations. Long-term forecasts of rainfall have been issued by the Indian government for many years, yet we also know of no empirical studies that document whether farmers respond to such forecasts and, if so, how that affects agricultural profitability.

In this paper we used newly-available panel data on farmers in India to estimate how the returns to planting-stage investments vary by rainfall realizations using an IV strategy in which the Indian forecast of monsoon rainfall serves as the main instrument. We show that the Indian forecasts significantly affect farmer investment decisions and that these responses account for a substantial fraction of the inter-annual variability in planting-stage investments, that the skill of the forecasts vary 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 indicate that Indian farmers on average under-invest, by a factor of three, when we compare actual levels of investments with the optimal investment level that maximizes expected profits over the full distribution of rainfall realizations.

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[18] We use the mean and standard deviation of monsoon rainfall from the CMIP3 mpi_echam5 model.

[19] This exercise does not take into account the effects of mean temperature changes associated with the global warming scenario, because we have no estimates of the effect of temperature variation on profits or input choice. The simulations of course assume that the parameters of the input demand and profit functions are stable; if farming practices are altered in response to the change in the rainfall distribution, our simulations understate the gains associated with the change.

We also used our estimates to quantify how farmers' responses to the forecast affect both the level and variability in profits relative to actual and optimal investments in a scenario in which there are no signals. These indicated that farmer's use of the forecasts increased average profit levels but also increased profit variability compared with farmers without access to forecasts. Indeed, based on the actual behavior of the farmers, our estimates indicated that they do better than farmers who would undertake optimal, unconstrained investments but have no forecasts when rainfall realizations are high, but worse under adverse rainfall conditions. Finally, we also assessed how profit levels would increase in the future as forecast skill increases under current climate conditions and under conditions predicted by climate models.[20] These exercises indicate that even modest skill improvements would substantially increase average profits, and slightly more so in a warmed climate.

The possibility of improvements in forecasting weather realizations has important consequences for the design of agricultural insurance. Conversely, the provision of agricultural insurance affects the responsiveness of farmers to weather forecasts. We have shown that farmers adjust their planting-season investments in response to skilled forecasts. 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 are 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 thus 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 quite 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*. In the context of our model with only 2 states and a forecast, complete insurance would be achieved with 3 insurance products, all sold before the revelation of the forecast: a conventional weather index product that pays out in the event of bad weather, and two forecast insurance policies, one that pays out in the event of bad weather after a forecast of good weather, and the other that pays out in the event of good weather after a forecast of bad. There would be demand for all three products at actuarially fair rates, and their combination would achieve complete insurance and productive efficiency. The response of planting-season

[20] As we noted in the introduction, the Indian government has launched the $48 million "Monsoon Mission" to improve forecasts in the next five years.

investment to the forecast would be larger with this set of insurance than without, and the gain in expected profits from increases in forecast skill would be larger.

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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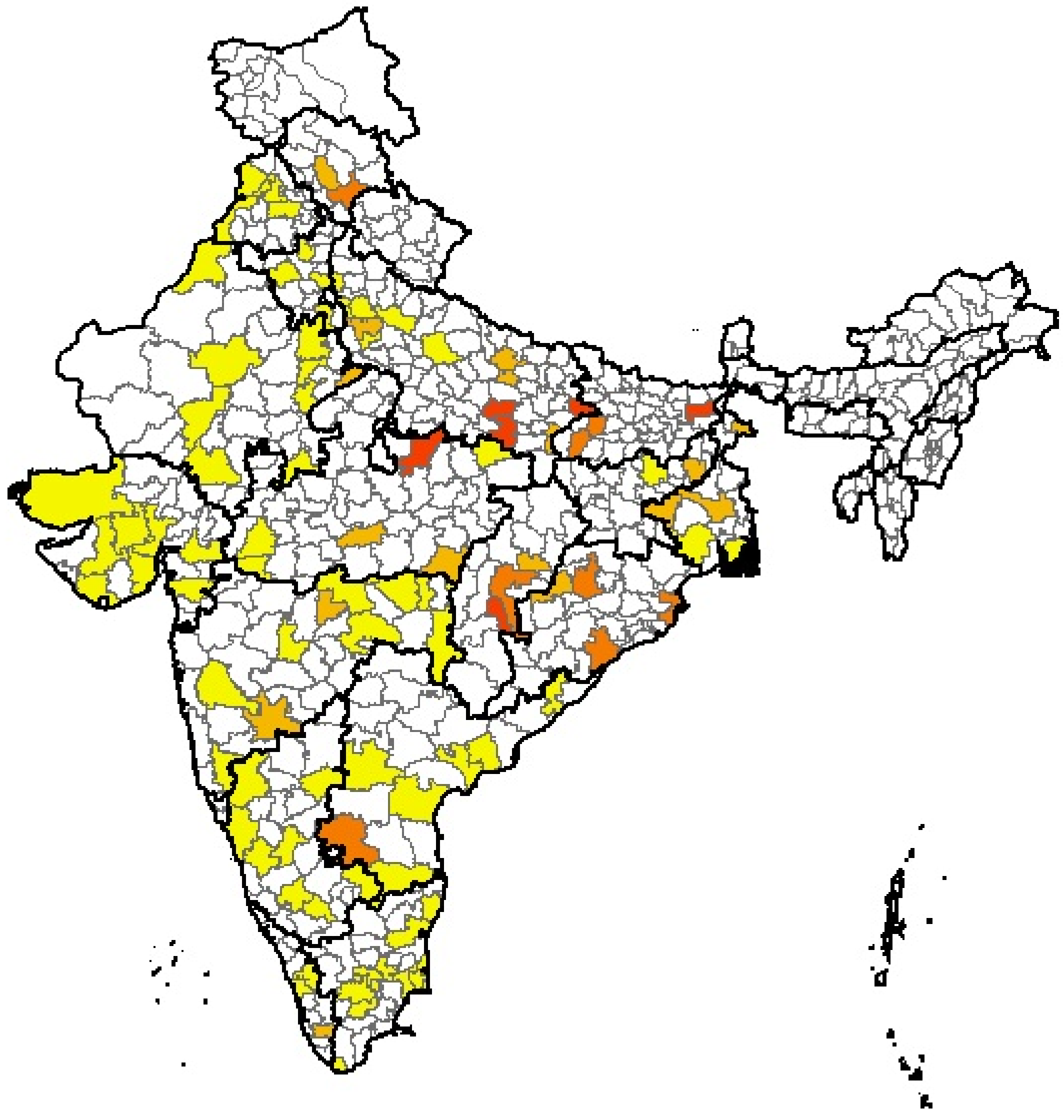
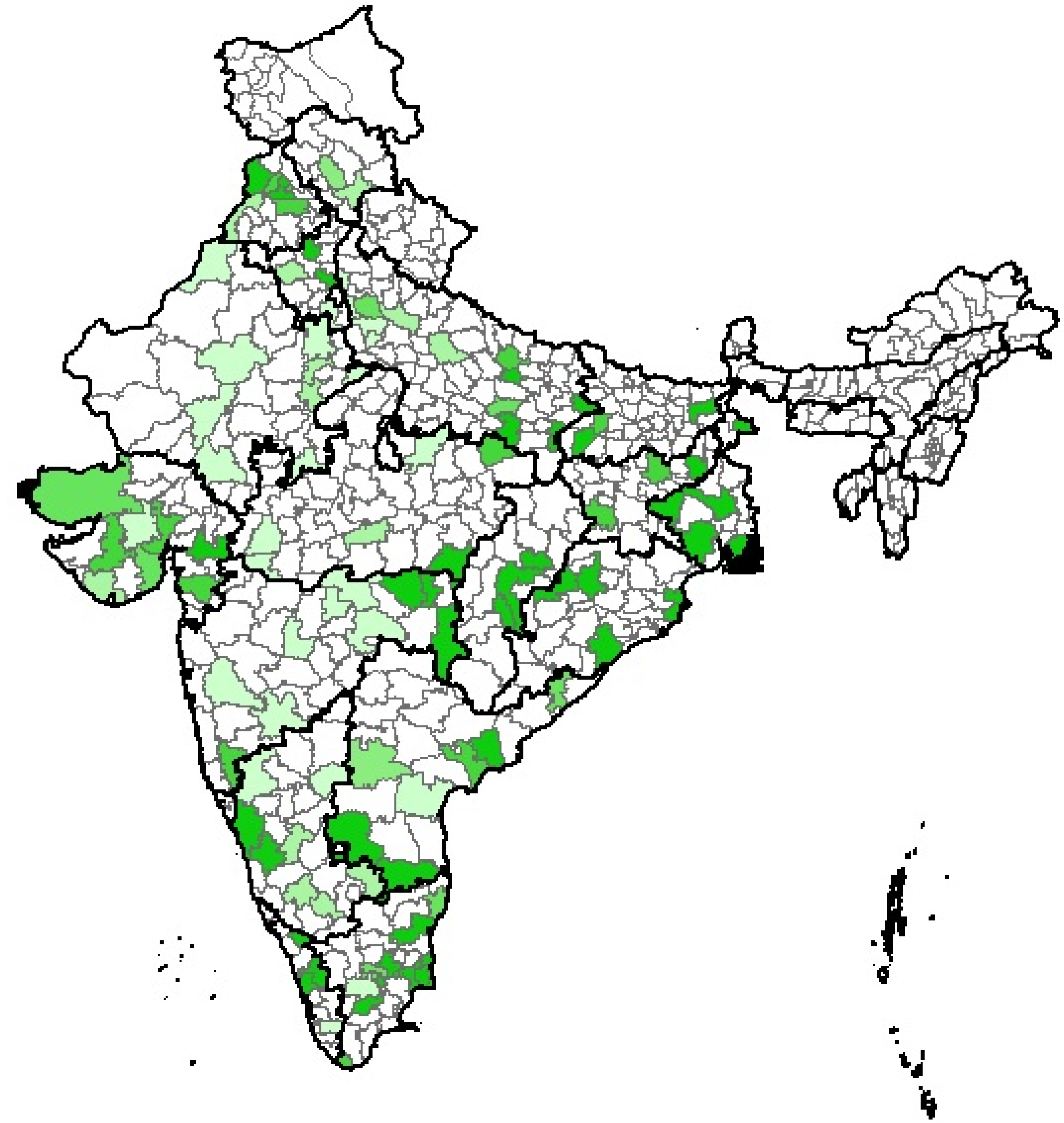
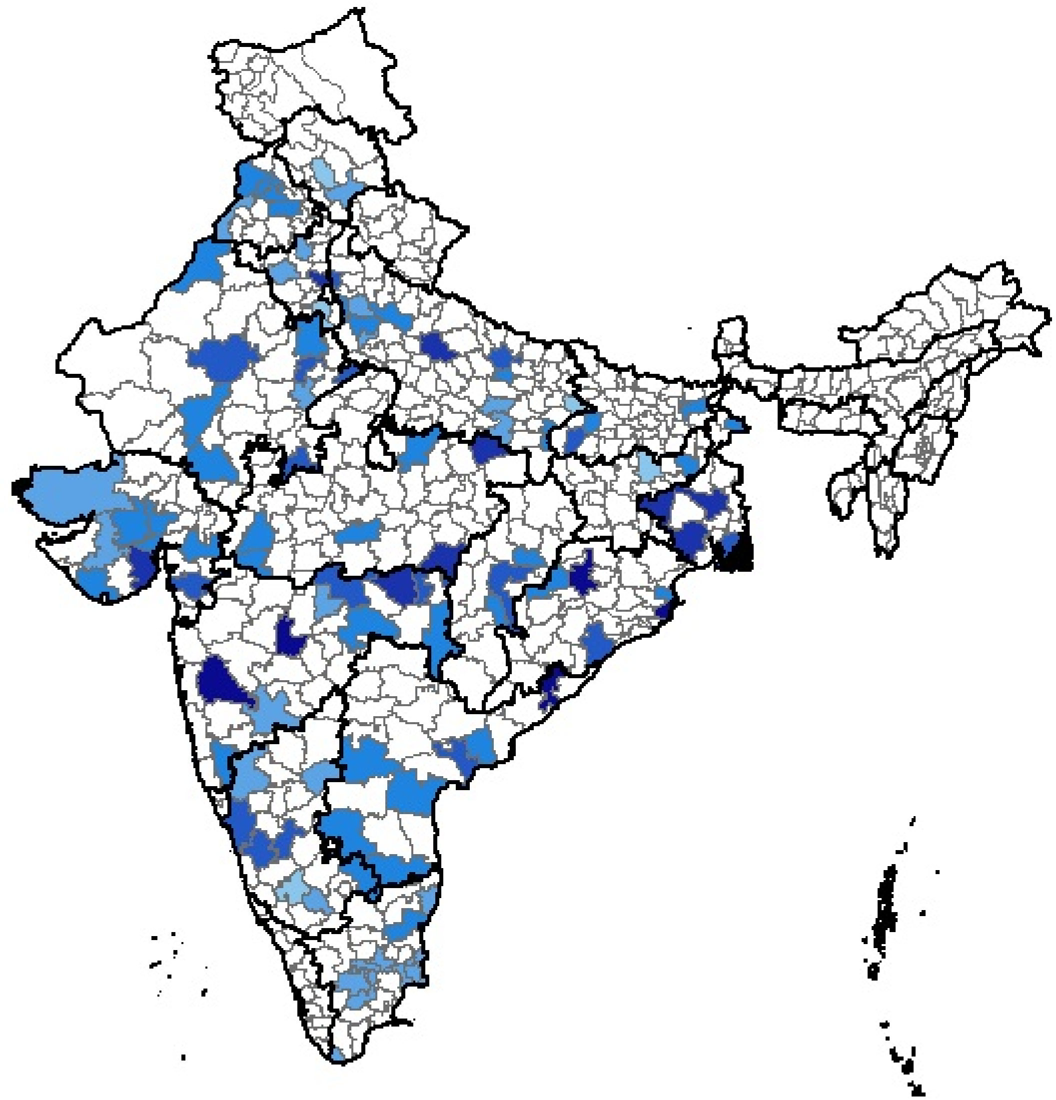
Map 1. Forecast Skill by District (REDS)



Map 2. Rice-Growing Areas by District (REDS)



Map 3. Rainfall CV by District (REDS)



Distributions of Planting Stage Investments

ICRISAT Panel, 2005-2011

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

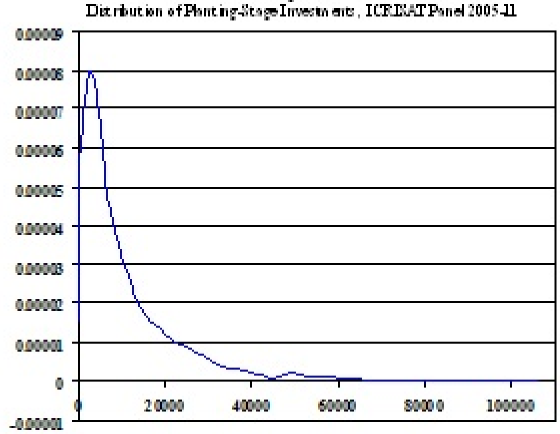
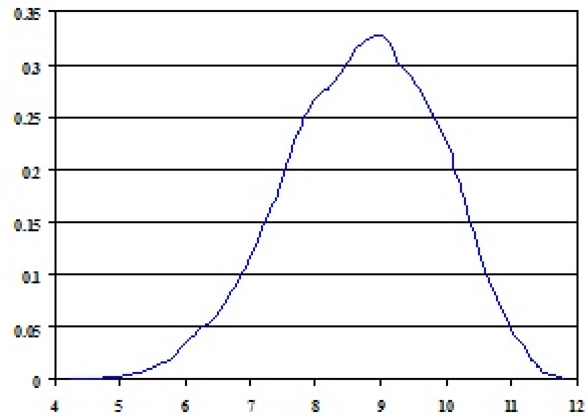


Figure 2
Distribution of Log Planting-Stage Investments, ICRISAT Panel 2005-2011



REDS Panel, 1999 and 2006

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

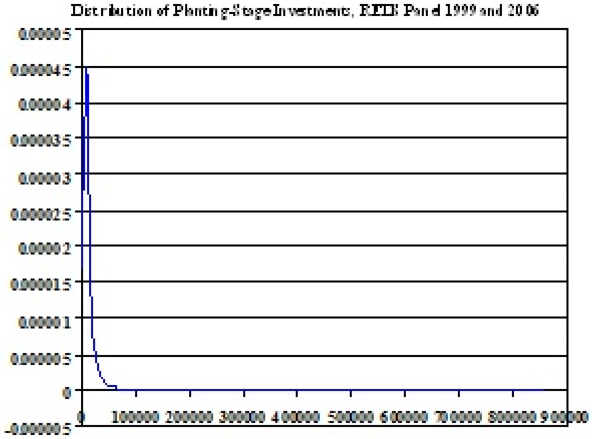


Figure 4
Distribution of Log Planting-Stage Investments, REDS Panel 1999 and 2006

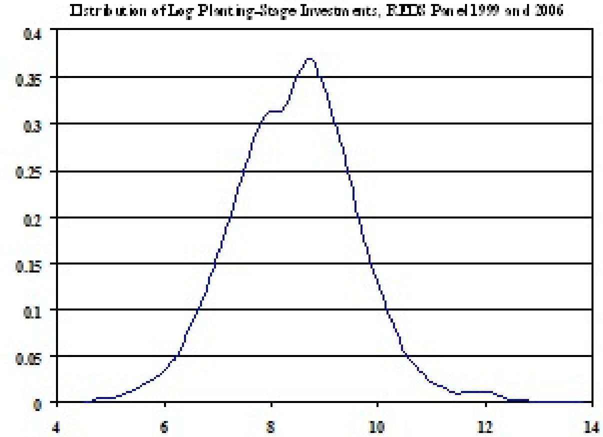


Figure 5
Relationship Between Crop-Year Farm Profits and *Kharif* Planting Investments ($x10^{-3}$), by Realized *Kharif* Rainfall

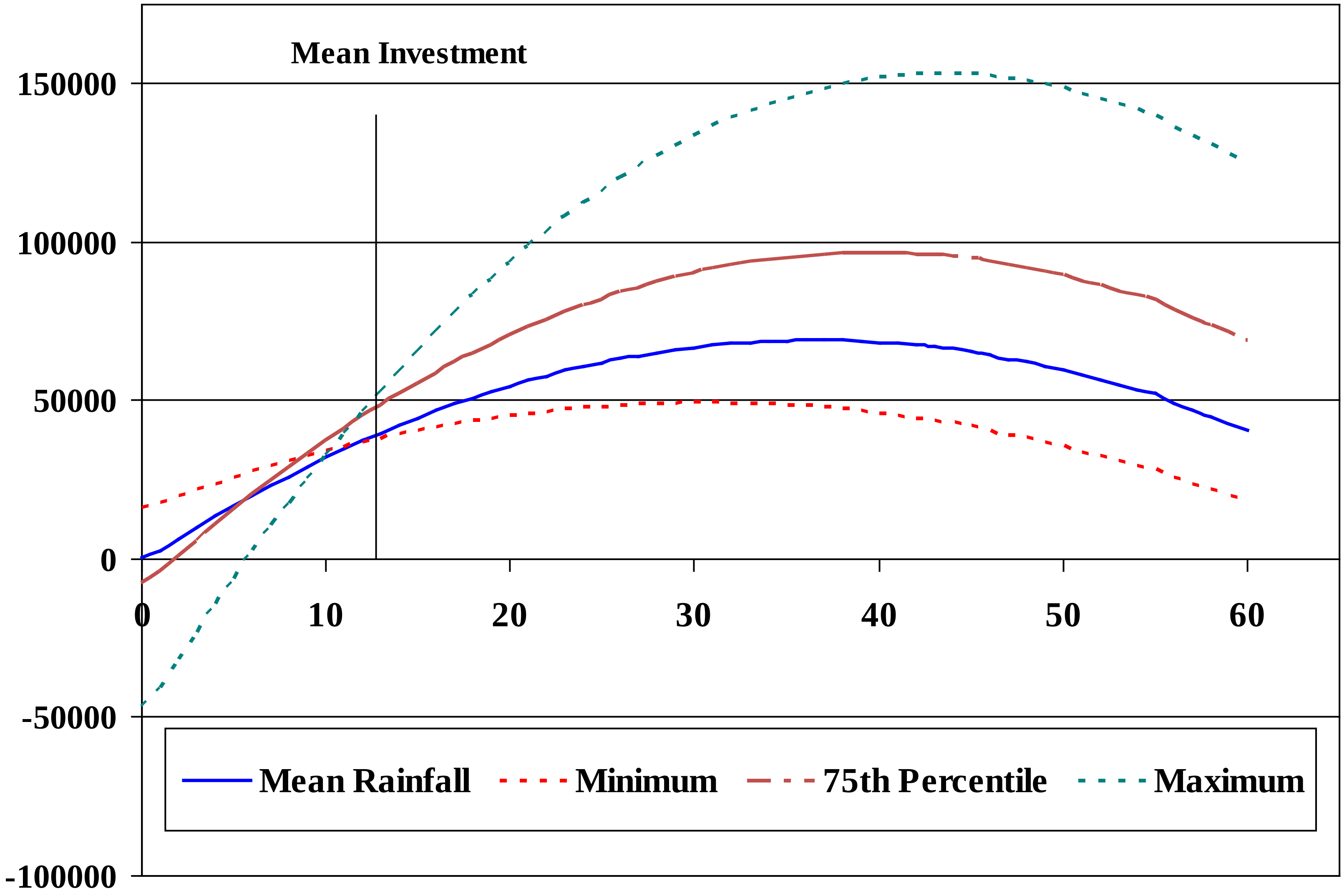


Figure 6. Simulated Planting-Stage Investments Over Time

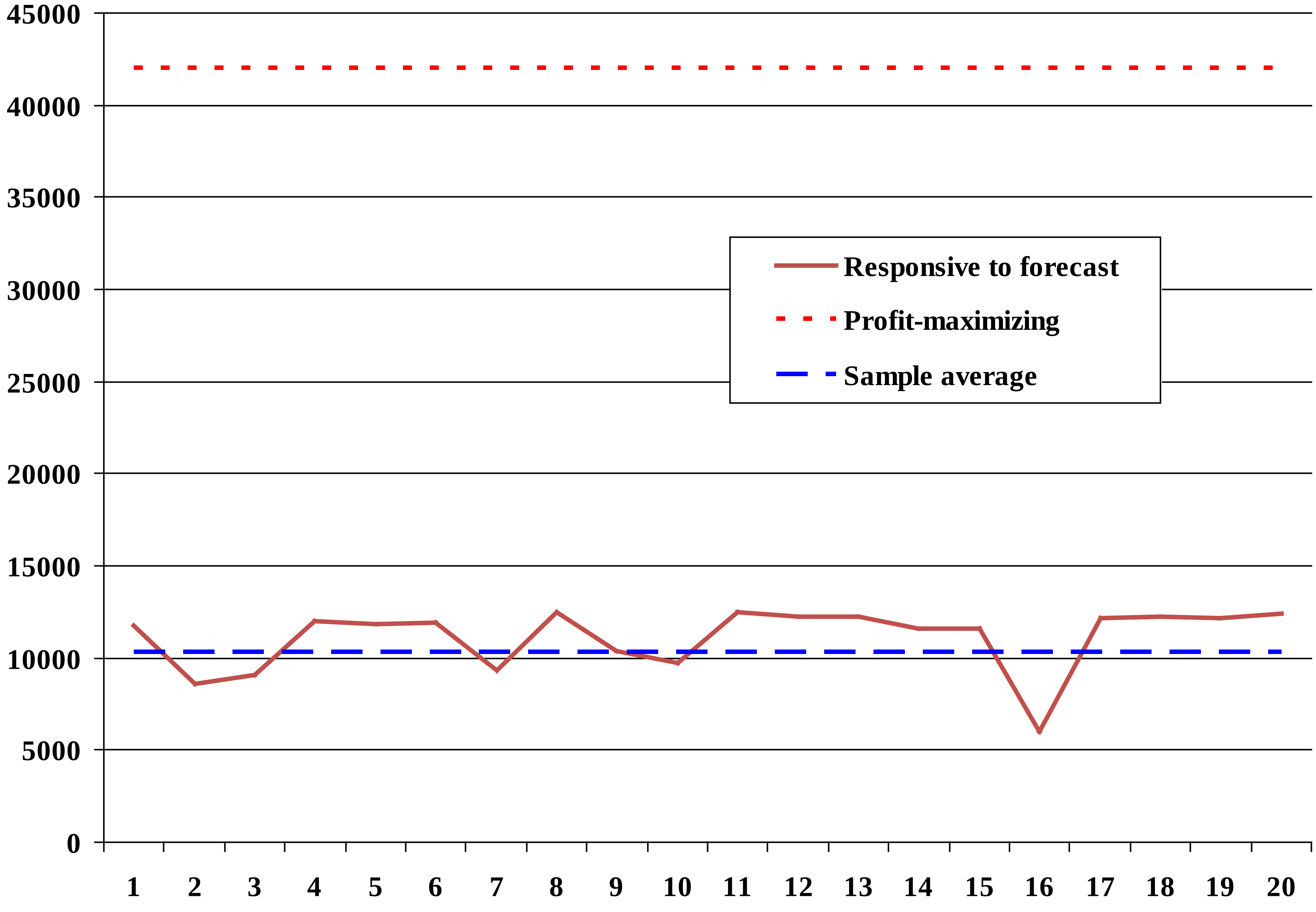


Figure 7. Simulated Profits Over Time

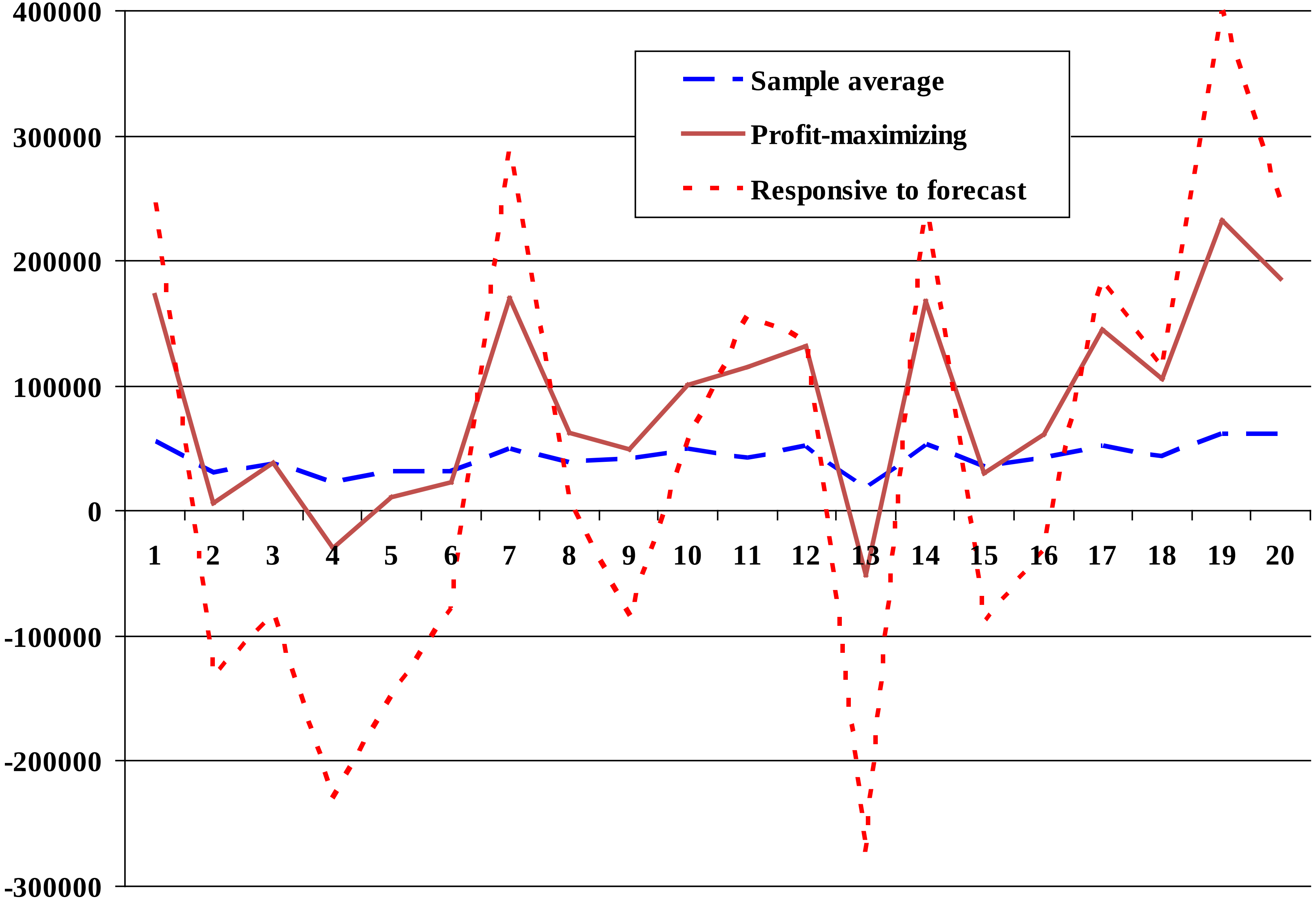


Figure 8. Profits by Forecast Skill and Scenario

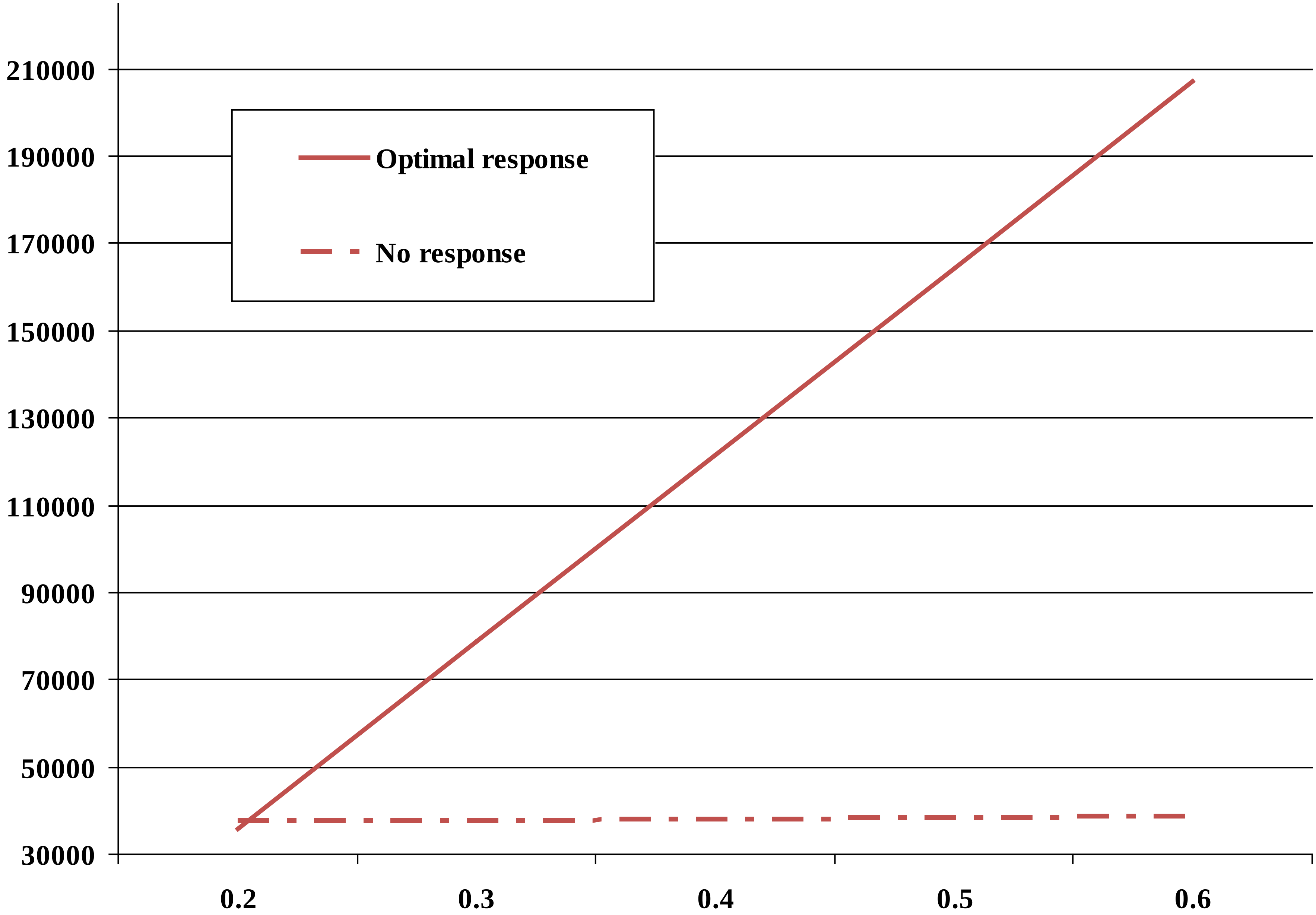


Figure 9. Profits by Forecast Skill and Scenario

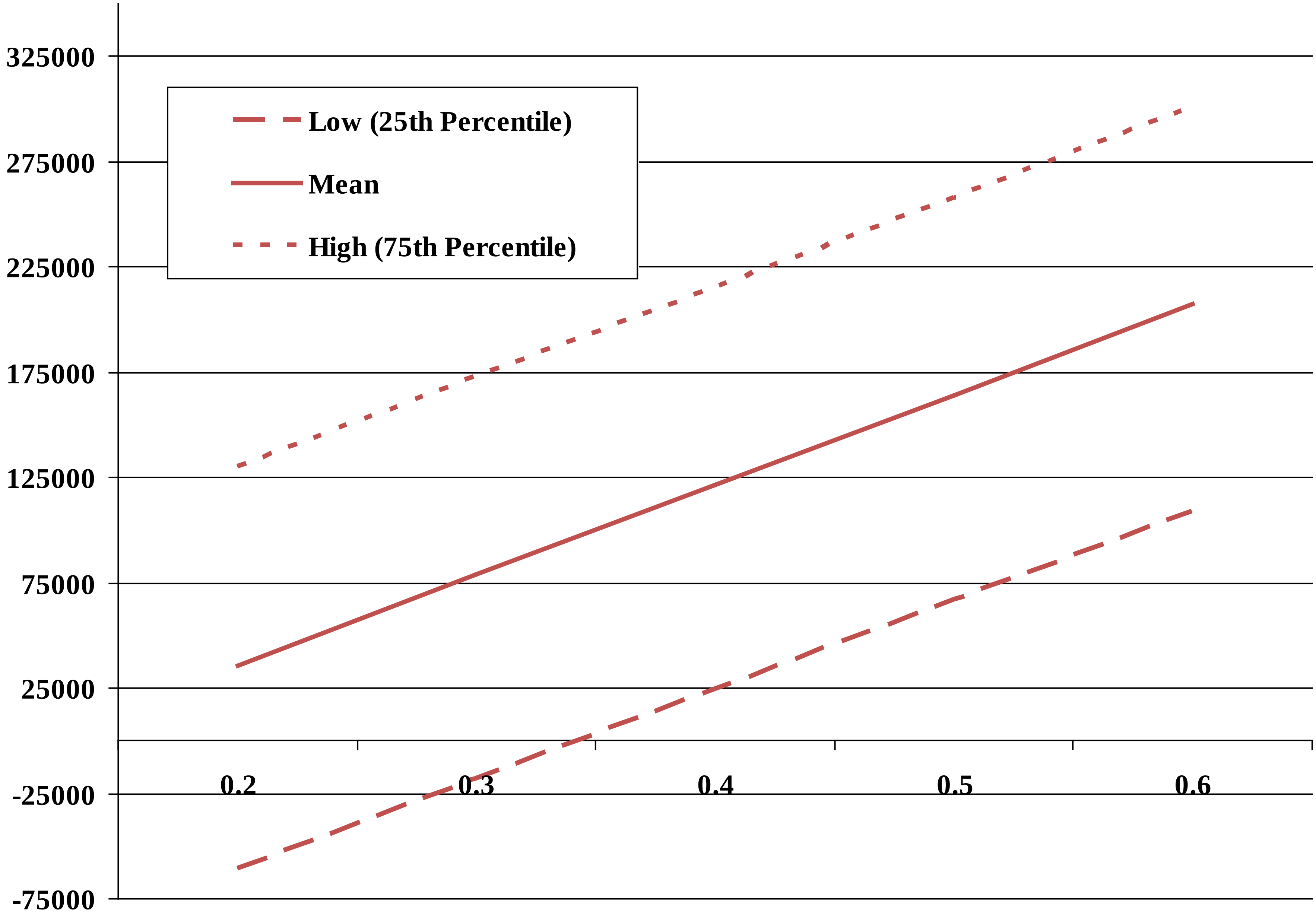


Figure 10. Profit Gain From a 0.1 Increase in Forecast Skill, by Rainfall Realization

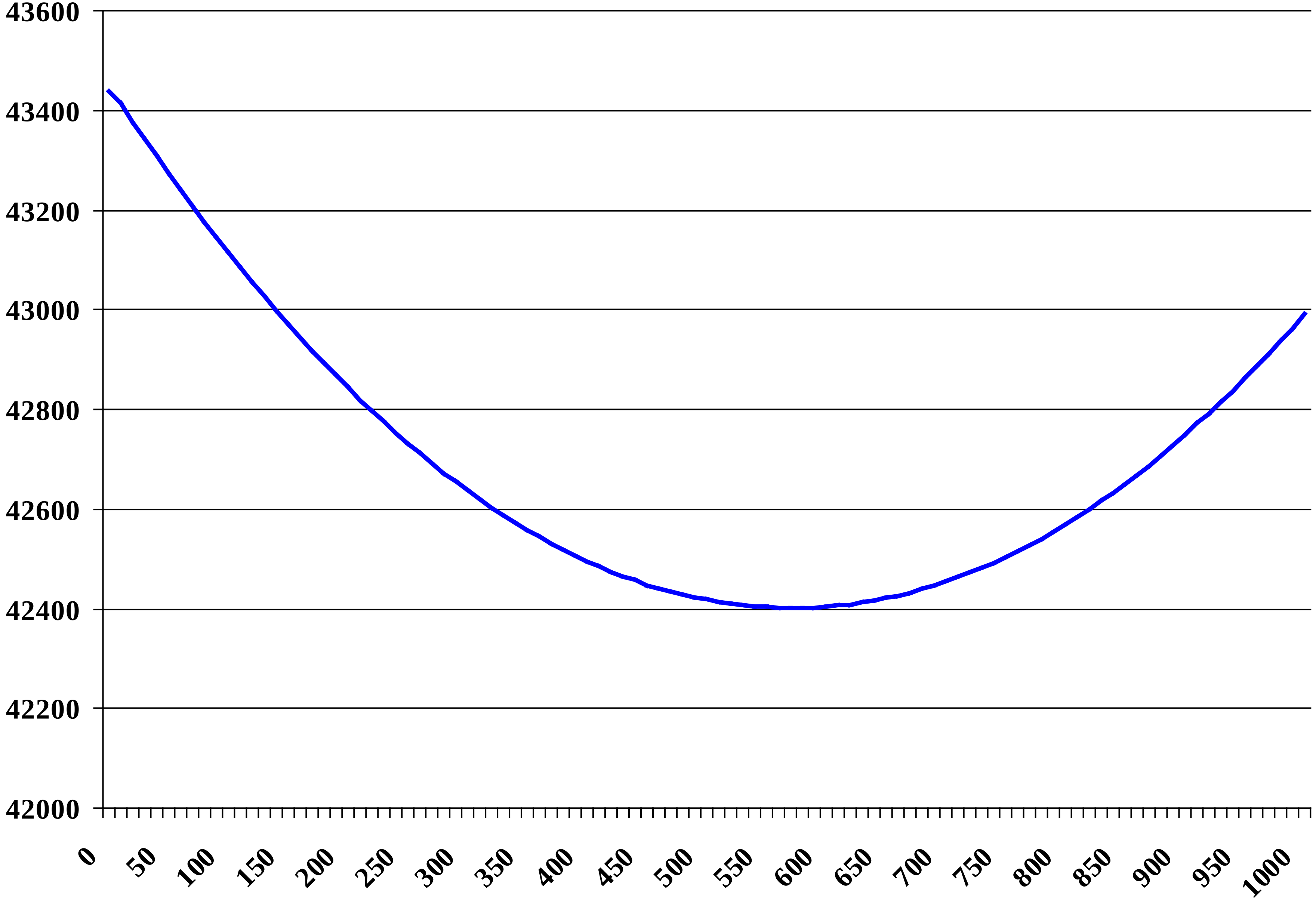


Figure 11. Profits by Forecast Skill and Scenario

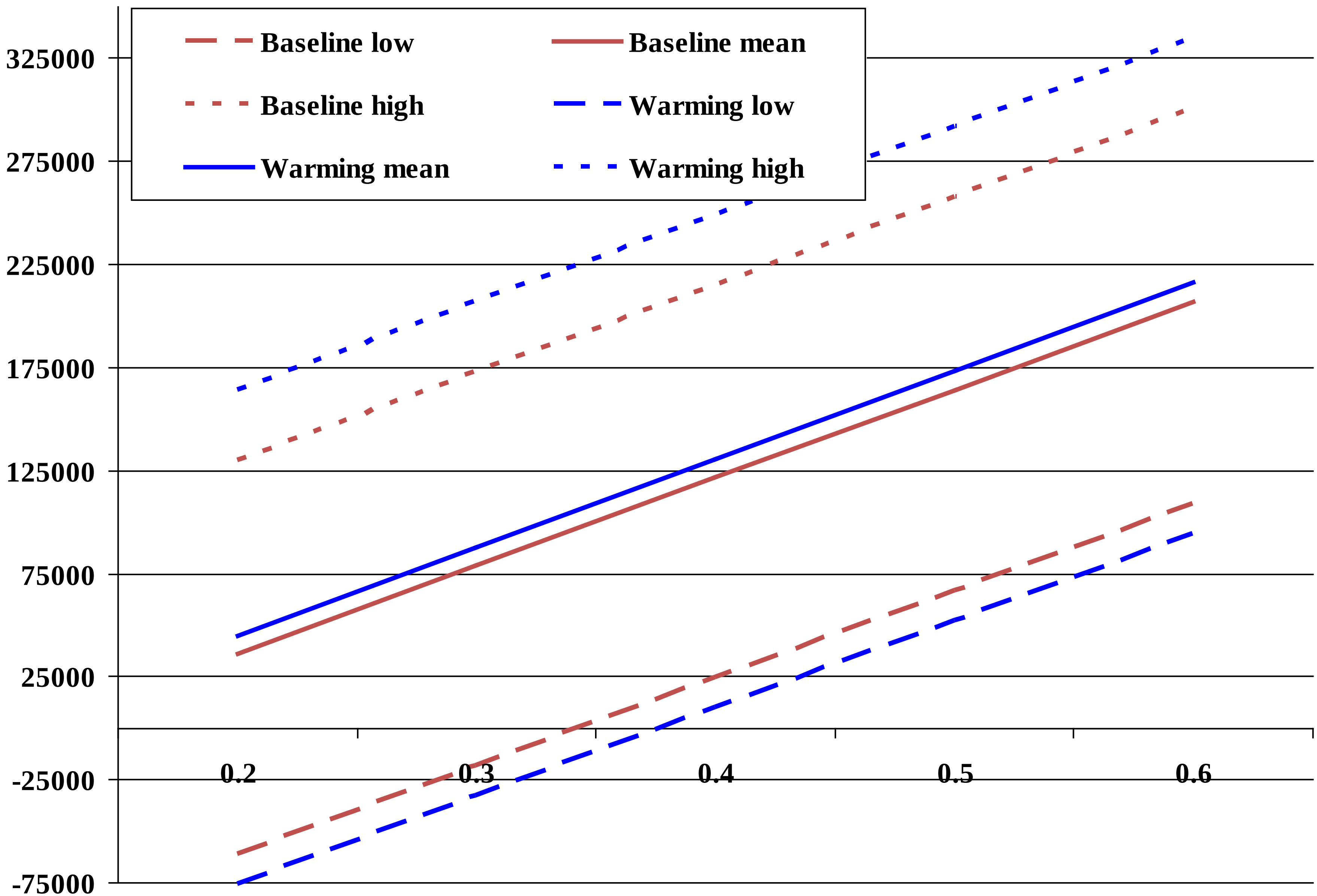


Table 1
Descriptive Statistics: ICRISAT Panel (2005-2011) and REDS Panel (1999 and 2006)

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 (SP forecast-rainfall correlation)	.451	.173	.193	.397	-.401	-.161

Table 3
Profit Function Estimates: The Returns to Planting-Stage Investments
(ICRISAT Panel, 2005-2011)

Estimation method/variable	FE	FE-IV	FE	FE-IV
Planting-stage investment	.922	3.38	-.0818	-.312
	(2.87)	(2.72)	(0.16)	(0.17)
Planting-stage investment x rainfall	-	-	.00195	.00840
			(2.49)	(2.72)
Planting-stage investment squared (x10^{-5})	-.556	-4.49	.982	-1.10
	(1.25)	(2.15)	(1.31)	(0.42)
Planting-stage investment squared x rainfall (x10^{-7})	-	-	-.281	-.837
			(2.58)	(1.90)
F-test: investment, investment squared=0 [*p*]	8.26	-	0.03	-
	[.004]		[.872]	
F-test: investment x rainfall, investment squared x rainfall=0 [*p*]	-	-	6.22	-
			[.013]	
$\chi^2(2)$ test: investment, investment squared=0 [*p*]	-	8.30	-	1.19
		[.016]		[.550]
$\chi^2(2)$ test: investment x rainfall, investment squared x rainfall=0 [*p*]	-	-	-	8.15
				[.017]
N	1667	1667	1667	1667

Absolute values of asymptotic *t*-ratios in parentheses. Specification also includes current-year annual and July-September rainfall, 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 and annual and July-September rainfall.

Table 4
Rainfall Forecasts, Profits and Planting-Stage Investments
(ICRISAT Panel, 2005-2011)

Estimation method	FE	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, 1-3	-18.7 (1.37)	.00052 (3.25)	.00067 (3.76)	-
Rain (*t*-1) x soil depth, > 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 log investment/*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 include the forecast interacted with land size, irrigation share, and four soil types.

Table 5
Rainfall Forecasts, Forecast Skill and Log Planting-Stage Investments
(REDS Panel, 1999 and 2006)

Estimation method/variable	FE	FE	FE	FE
Forecast rain	-.0670 (1.60)	-.122 (1.47)	-.125 (1.89)	-.153 (1.54)
Forecast rain x skill	.168 (2.53)	.482 (4.28)	.495 (4.22)	.570 (3.41)
Forecast rain*irrigated land share	-	.0839 (1.23)	.0800 (1.13)	.0767 (1.12)
Forecast rain*skill* irrigated land share	-	-.383 (3.55)	-.348 (3.17)	-.354 (3.08)
Forecast rain x rice area	-	-	.0264 (0.027)	.0306 (0.31)
Forecast rain x skill x rice area	-	-	-.0836 (0.63)	-.100 (0.75)
Forecast rain x rainfall CV	-	-	-	.00010 (0.75)
Forecast rain x skill x CV	-	-	-	-.00023 (0.86)
d log investment/*d*forecast (*t*) at skill=.43	.00538 (0.38)	.0851 (0.98)	.0879 (1.64)	.0916 (1.77)
N	4438	4438	4438	4438

Absolute values of asymptotic *t*-ratios in parentheses clustered a at the forecast area level.

Appendix Map A

India Meteorological Department

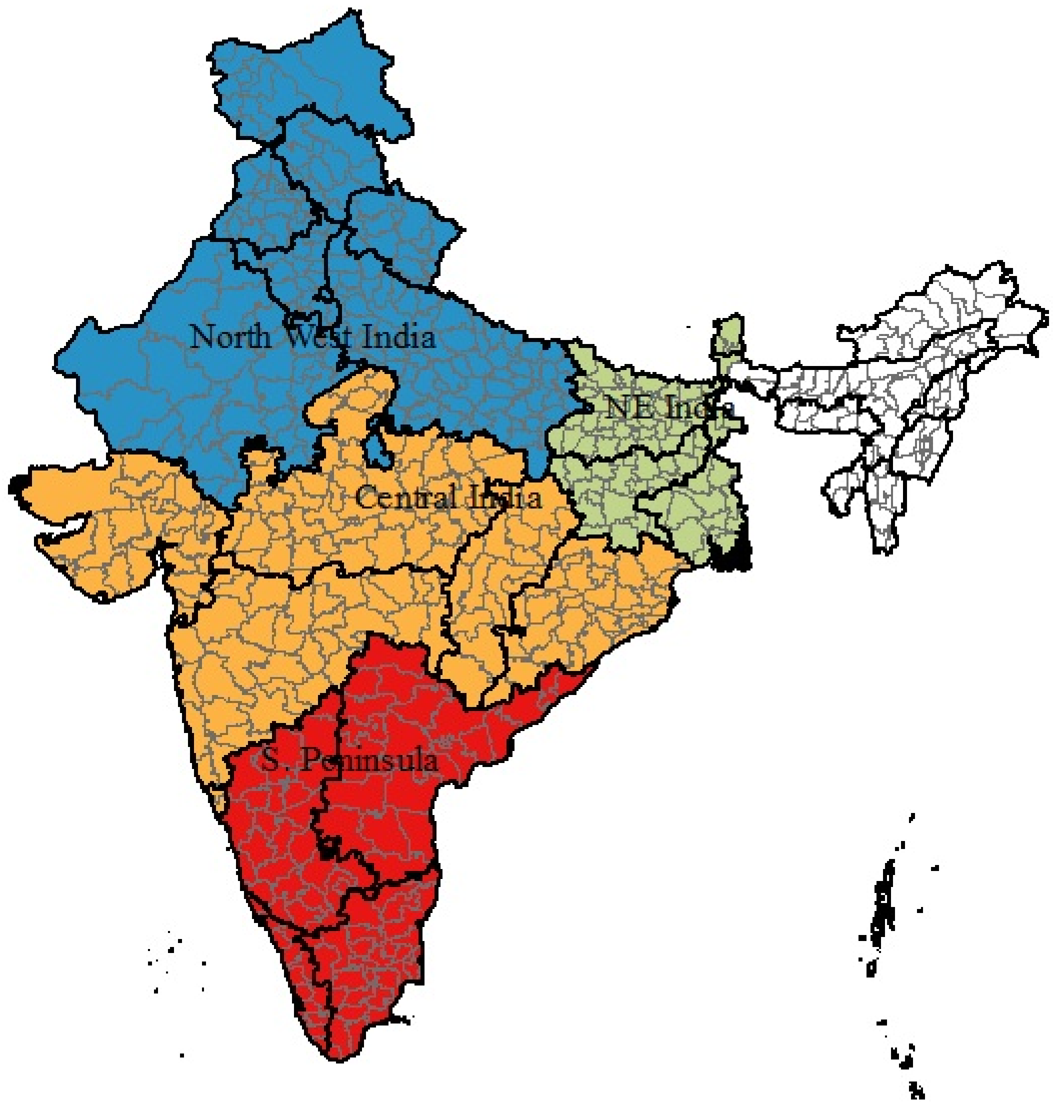


Table A
Savings Accounts of ICRISAT Households and Annual Interest Rates,
Weighted by Account Value

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