Forecasting Profitability

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- news: ag profits depend on weather
- Huge literature in development economics on
  - ex post mechanisms for dealing with risk
  - ex ante consequence of uninsured risk for investment, production, household organization choices
- Little work on reducing risk via better forecasting
  - a.f. insurance permits farmers to ignore risk: chose production to max expected profits
  - Perfect forecasting is even better: permits the farmer to make optimal production choices conditional on the realized weather

- Lots of qualitative evidence that farmers demand forecasts
- IMD forecast + national Monsoon Mission
- “New” ICRISAT VDSA surveys 2005-11 (but ongoing…) show CV of prep/planting investment of 54%%
    - Lagged profits (+credit constraints/risk)
    - Lagged rain (moisture overhang)
    - Changing input prices, expected output prices
    - Changing expectations of weather realizations

- Need to know returns to investment, technological innovation, interventions
- In agriculture, these depend on realization of stochastic events, most obviously weather
- Well-identified estimates of returns tend to be from a single season, in a small region
    - Karlan et al (2013)
    - Foster Rosenzweig *AER* (1996)
    - Duflo, Kremer, Robinson *AER* (2011)
    - Banerjee et al (2013); Bloom et al (2012), de Mel et al (2008, 2009)

- Reforms, Weather and Productivity in China
    - Lin (*AER* 1992) argues that ag output in China increased by 50% as a consequence of reforms
        - Estimates based on a production function, with before/after years
    - But weather variation also matters for productivity
    - Zhang and Carter (*AJAE* 1997) show that chance improvements in weather over the reform period also matter.
        - They attribute 38% of growth to reforms

- Std errors substantially overstate precision of return estimates
- Broad geographic scope can provide variation, but now we are worried that unobserved attributes may be correlated with weather realizations
- Panel data

What we do

- Model
  - Risk-averse farmers optimally respond to forecasts
  - How do these responses vary by skill of forecast?
- Use long-range forecasts of IMD + Panel Data on farmers
  - Assess the geographical variation in skill of forecast
  - Estimate returns to planting stage investments
    - By rainfall realization
    - Key instrument is the IMD long range forecast
  - Show responsiveness of investment to forecast, interacted with skill
  - Use simulations to show return to improvements in forecast skill, with and without climate change
- Implications for design of insurance

Modelling weather risk and forecasts

- Land prep/planting investment *x*
- $S \in \{b, g\}\ prob(S = b) = \pi$
- with

$$f_s(x)$$

$$f_b(x) < f_g(x)$$

$$\frac{\partial f_b(x)}{\partial x} < \frac{\partial f_g(x)}{\partial x}$$

- Forecasts! *B* or *G* before *x* is chosen

  prob(S=b|B)=prob(S=g|G)=q

- Hence the problem, conditional on forecast F is

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

- Subject to

$$c^0 = Y - x - a$$

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

Choices of *a* and *x* satisfy

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

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

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

- Profit max would imply

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

- Risk averse farmer insists on expected return to *x* greater than *r.* From the FOC for *a* and *x:*

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

$$<qEu'(c^1)\frac{\partial f_b}{\partial x}+(1-q)\,\mathrm{E}\,u'(c^1)\frac{\partial f_g}{\partial x}$$

hence

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

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

Follows directly from comparative statics of the FOC for *a* and *x*

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

$$< 0$$

Similar exercise shows *a* rises with *q.*

Since $prob(S=b|B)=prob(S=g|G)=q$,

$$x((1-q)|G) \equiv x(q|B)$$
$$a((1-q)|G) \equiv a(q|B).$$

so

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

and with $q>0.5$, $x(q|G)>x(q|B)$.

Analogous reasoning shows $a(q|G)<a(q|B)$

- **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.*

We showed above that

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

$$\frac{d(x(q\,|\,\mathrm{B})}{dq} < 0$$

Hence

$$\frac{d(x(q\,|\,G)}{dq} - \frac{d(x(q\,|\,B)}{dq} > 0.$$

- **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.*

$$
\begin{aligned}
\frac{dx(q\,|\,B)}{dY} &= \frac{-\beta r u''(c^0)}{\det}\left(q u''(c_b^1)\left(r - \frac{\partial f_b}{\partial x} \right) + (1-q) u''(c_g^1)\left(r - \frac{\partial f_g}{\partial x} \right) \right) \\
&> \frac{-\beta r u''(c^0)}{\det}\left(q u''(c_b^1)\left(r - \frac{\partial f_b}{\partial x} \right) + (1-q) u''(c_b^1)\left(r - \frac{\partial f_g}{\partial x} \right) \right) \\
&= \frac{-\beta r u''(c^0) u''(c_b^1)}{\det}\left(q\left(r - \frac{\partial f_b}{\partial x} \right) + (1-q)\left(r - \frac{\partial f_g}{\partial x} \right) \right) \\
&> 0
\end{aligned}
$$

The first inequality depends on DARA; the second inequality relies on proposition 1. The same arguments hold after a forecast of good weather.

- **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.*

With irrigation, $f_g(x) \equiv f_b(x)$.

so *x(q|G)=x(q|B).* By prop 3, as skill of forecast increases, difference in responsiveness of farms with and without irrigation to a forecast of good weather grows.

- **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.*

Need new notation and let prob of good weather be 1/2:

$$f_g(x) = \widetilde{f_g}(x) + \gamma,\ f_b(x) = \widetilde{f_b}(x) - \gamma$$

An increase in γ is a mean preserving spread

$$\frac{dx(B)}{d\gamma} = \frac{-\beta u''(c_0)}{\det(\mathrm{B})}\left(-qu''(c_b^1)\left(\frac{\partial f_b}{\partial x} - r\right) + (1-q)u''(c_g^1)\left(\frac{\partial f_g}{\partial x} - r\right)\right)$$
$$< 0.$$

The inequality follows because

$$\frac{\partial f_b(x)}{\partial x} < r < \frac{\partial f_g(x)}{\partial x}$$

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

Let the probability of good weather be .5

Then

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

1st 2 terms are positive by direct effect of matching; 2nd 2 terms by effect of improved forecasts on reducing risk

And for expected utility,

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

The Data Sets

We use two panel data sets that provide stage-specific agricultural investments

A. The ICRISAT Village Dynamics in South Asia (VDSA): 2005-2011
   1. Six villages located in the states of Maharashtra and Andhra Pradesh
   2. Information on inputs and outputs collected at high frequency over the crop year (every three weeks)
      1. We aggregate all *kharif*-season planting stage investments July/Aug.
      2. Investments informed by and relevant to the IMD forecast
   3. Information on daily rainfall for each village over all the years
      1. We can compute period-specific totals of rainfall
      2. July-September totals (predicted by IMD) and crop-year totals
   4. 477 farmers appearing in at least two consecutive years (1,667 observations)

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

1. Carried out by the National Council of Economic Research in 242 villages in the 17 major states of India (not Assam, J&K)
2. Agricultural inputs collected by stage and season, so we can also compute *kharif* planting-stage investments
3. Information on monthly rainfall by village for each year 1999-2006
    1. No information on rainfall at the end of the harvest season for which there is profit data, so it is not possible to estimate profit function
    2. Can assess IMD forecast skill by region (July-September rain)
4. Can estimate the response of farmer investments to forecast by forecast skill
5. 2,219 farmers (4,438 observations)

Tables 1A and 1B display descriptive statistics for each data set

Notable features:

A. ICRISAT farmers investment has less variability than rest of India (REDS sample)
B. Distribution of investments is similar (log-normal: Figures 1-4)
C. Intertemporal crop-year rainfall CV in ICRISAT villages is 2X that for all of India
D. Fraction of irrigated land is lower for ICRISAT farmers by 26%; rainfall variability matters more

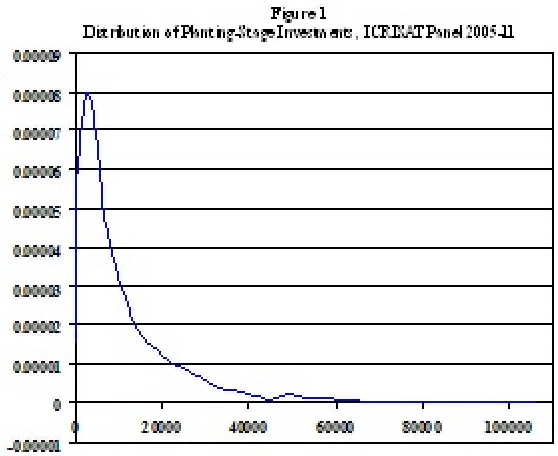
Profit measure: value of agricultural output less the value of all inputs, including the value of family labor and owned input services

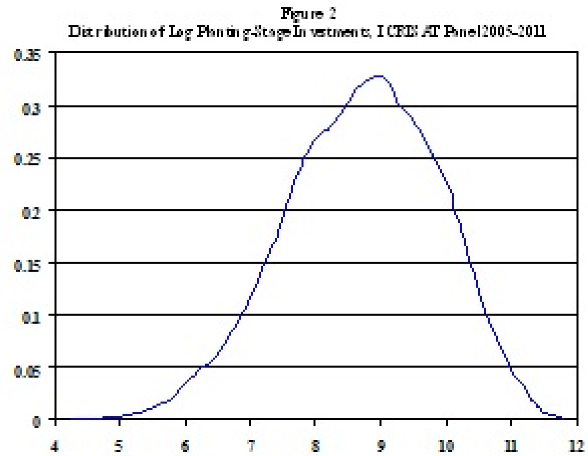
Discount rate based on real return on savings (85% of households have a positive balances: Table A

Average nominal i=10.4%, inflation rate=10.6% over the period; we set r=1

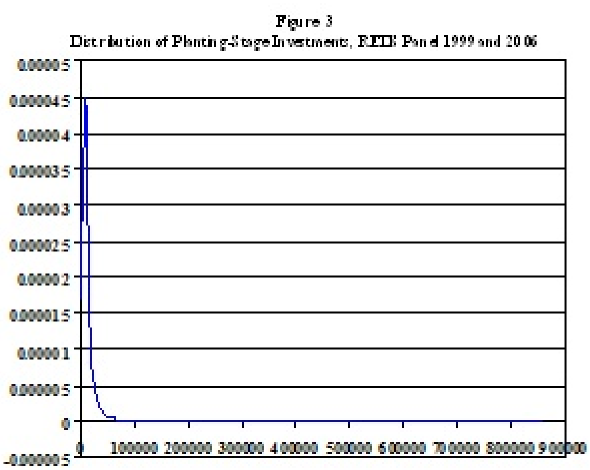
Distributions of Planting Stage Investments

ICRISAT Panel, 2005-2011





REDS Panel, 1999 and 2006



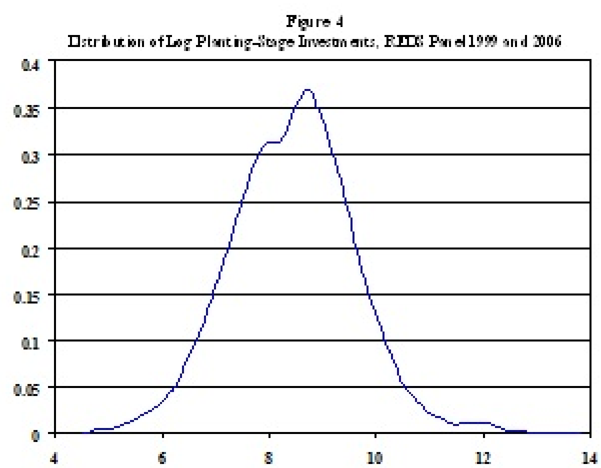


Table 1A
Descriptive Statistics: ICRISAT Panel, 2005-2011

Variable	Mean	Sd
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	

Table 1B
Descriptive Statistics: REDS Panel, 1999 and 2006

Variable	Mean	Sd
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	2,219	

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

IMD Monsoon Forecasts and Forecast Skill

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

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

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

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

First forecast, and subsequent forecasts, based on snow cover in the Himalayas, pre-Monsoon weather conditions in India and over the Indian Ocean and Australia

Farmers unlikely to have this formation

Until 2013 there have been no alternative formal sources of monsoon forecasts

What is the skill of these forecasts?

IMD publishes the history of forecasts and actual rainfall starting in 1932

Forecasts are by region, but the regions have changed over time and regional forecasting was abandoned in the period 1988-1998

The forecasting models (all statistical) have changed over time

Starting in 1999, forecasts are all quantitative and the regions are stable

For 1999-2010, using IMD published data:

A. Forecast skill is not high
B. Symmetry property assumed in the model holds:
   Whether a below- or above-normal forecast, slightly greater than 50% chance the forecast is correct
C. But, forecast skill varies by region, and for some regions the forecast has skill

1999-2003: forecasts issued for three regions

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

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

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

A. For the Maharashtra villages, skill is relatively high (ρ =.267)
B. For the Andhra Pradesh villages, worthless (not because variability is higher)

Map 1: shows based on the 242 REDS villages (1999-2006), where the forecast has skill

A. Overall correlation is .132, ranging from .01 to .77
B. Broad contiguous geographical regions where the skill is higher

Appendix Map A

India Meteorological Department

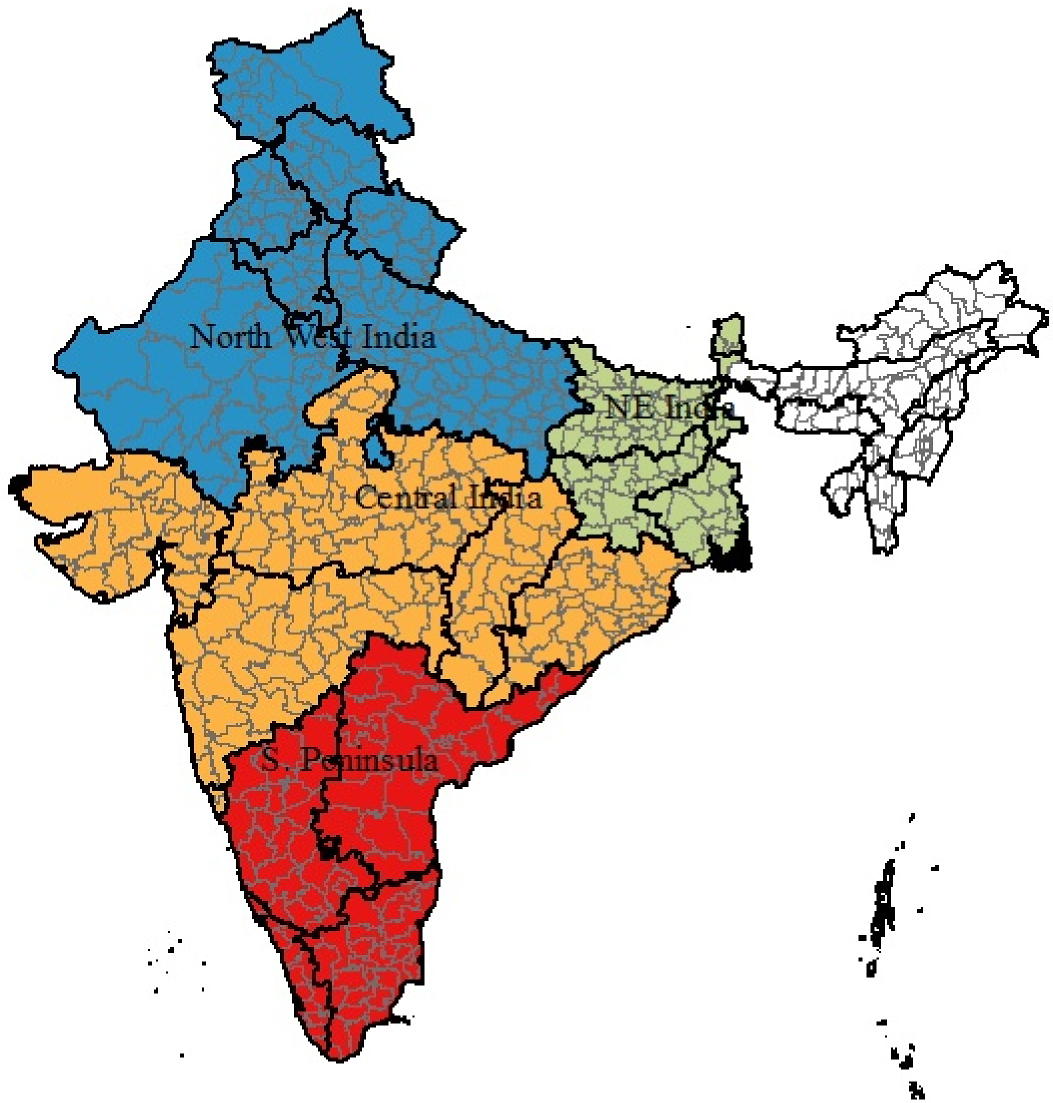
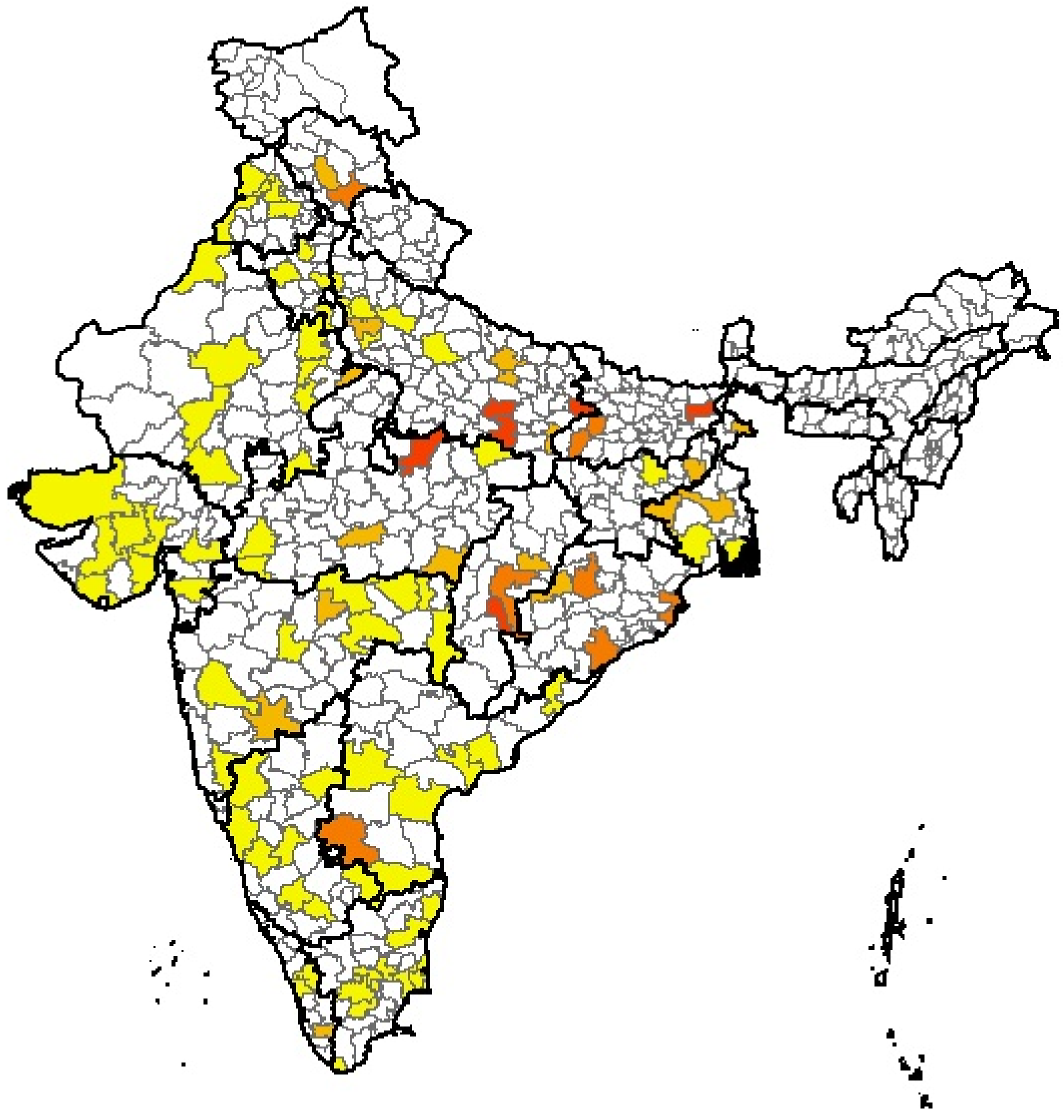


Table 2
Forecast Skill and Rainfall Characteristics, ICRISAT Villages 2005-2011, by Village

State	Maharashtra				Andhra Pradesh	
Village	Kalman	Kanzara	Kinkheda	Shirapur	Aurepalle	D okur
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 ϱ)	.451	.173	.193	.397	-.401	-.161

Map 1. Forecast Skill by District (REDS)



We estimate

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

Key exclusion restriction is the forecast itself

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

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	1,667	1,667	1,667	1,667

Figure 5
Relationship Between Crop-Year Farm Profits and *Kharif* Planting Investments ($\times 10^{-3}$), by Realized *Kharif* Rainfall

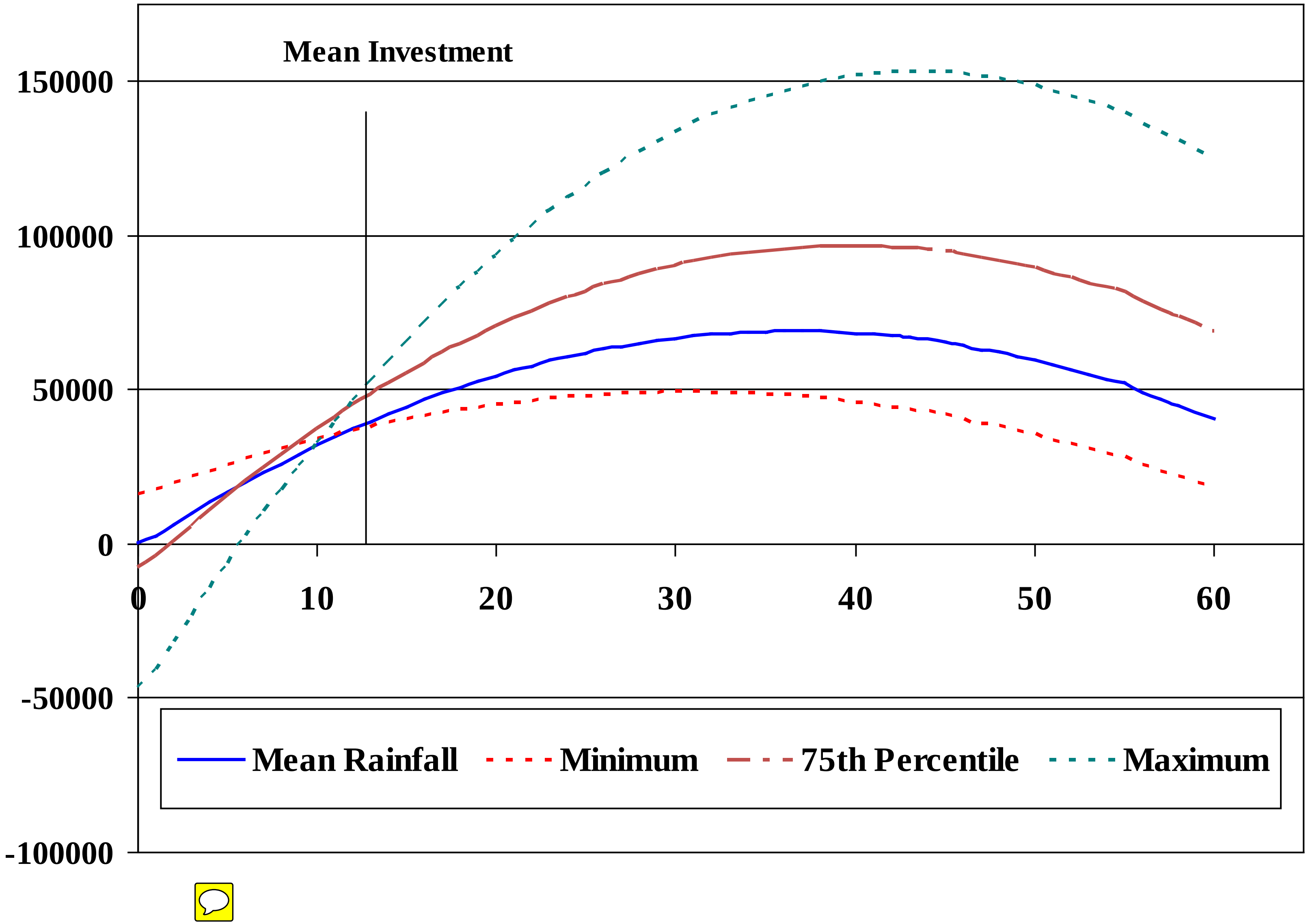


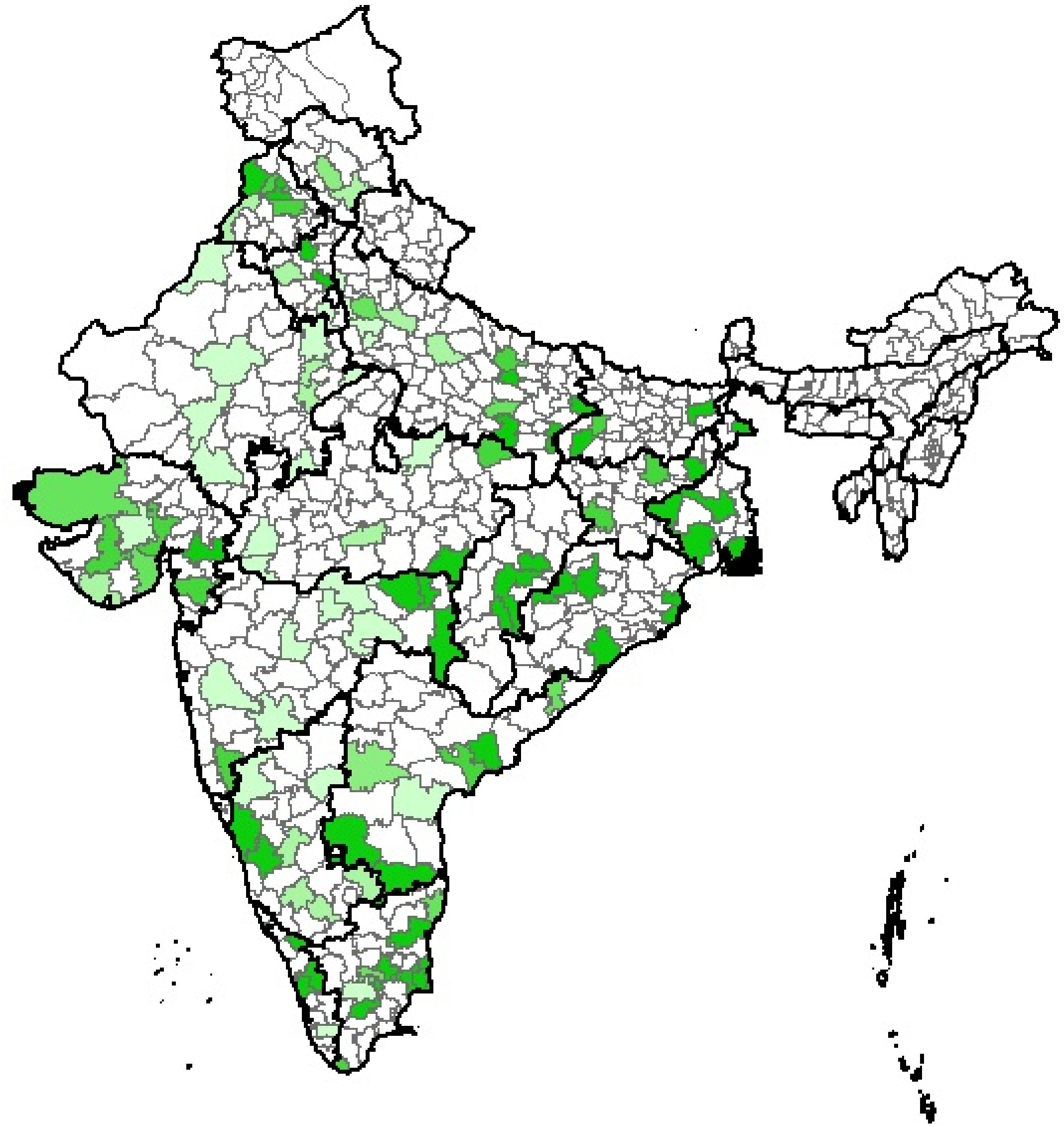
Table 4
Rainfall Forecasts, Profits and Planting-Stage Investments, ICRISAT Panel

Estimation method	FE	FE-IV		
Variable	Profits (*t*-1)	Log planting-stage investments (*t*)		
Sample	All Villages		Maharasthra	Andhra Pradesh
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	1,399	1,399	974	425

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	-.122	-.125	-.153
	(1.60)	(1.47)	(1.89)	(1.54)
Forecast rain x skill	.168	.482	.495	.570
	(2.53)	(4.28)	(4.22)	(3.41)
Forecast rain*irrigated land share	-	.0839	.0800	.0767
		(1.23)	(1.13)	(1.12)
Forecast rain*skill* irrigated land share	-	-.383	-.348	-.354
		(3.55)	(3.17)	(3.08)
Forecast rain x rice area	-	-	.0264	.0306
			(0.027)	(0.31)
Forecast rain x skill x rice area	-	-	-.0836	-.100
			(0.63)	(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	.0851	.0879	.0916
	(0.38)	(0.98)	(1.64)	(1.77)
N	4,438	4,438	4,438	4,438

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



Map 3. Rainfall CV by District (REDS)

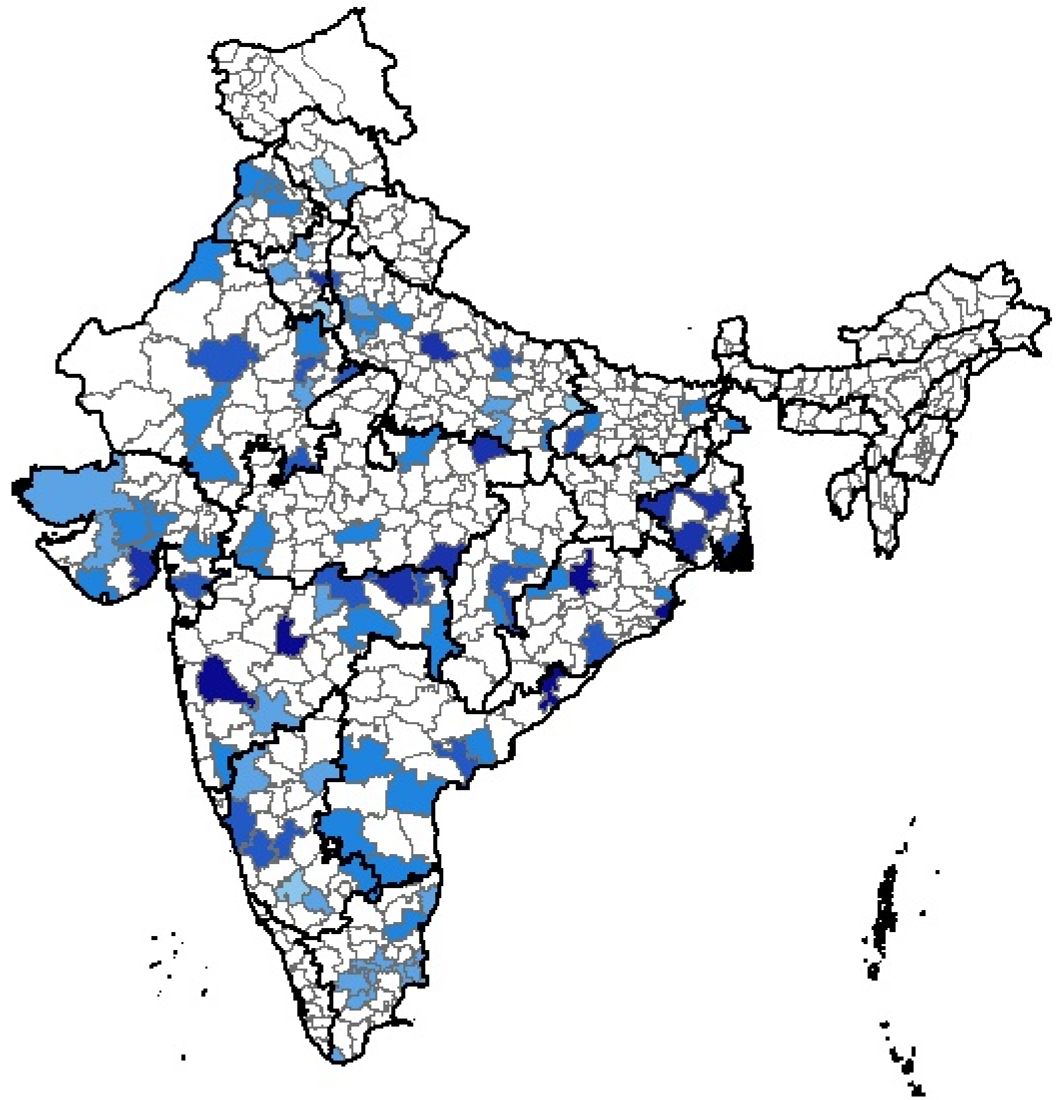


Figure 6. Simulated Planting-Stage Investments Over Time

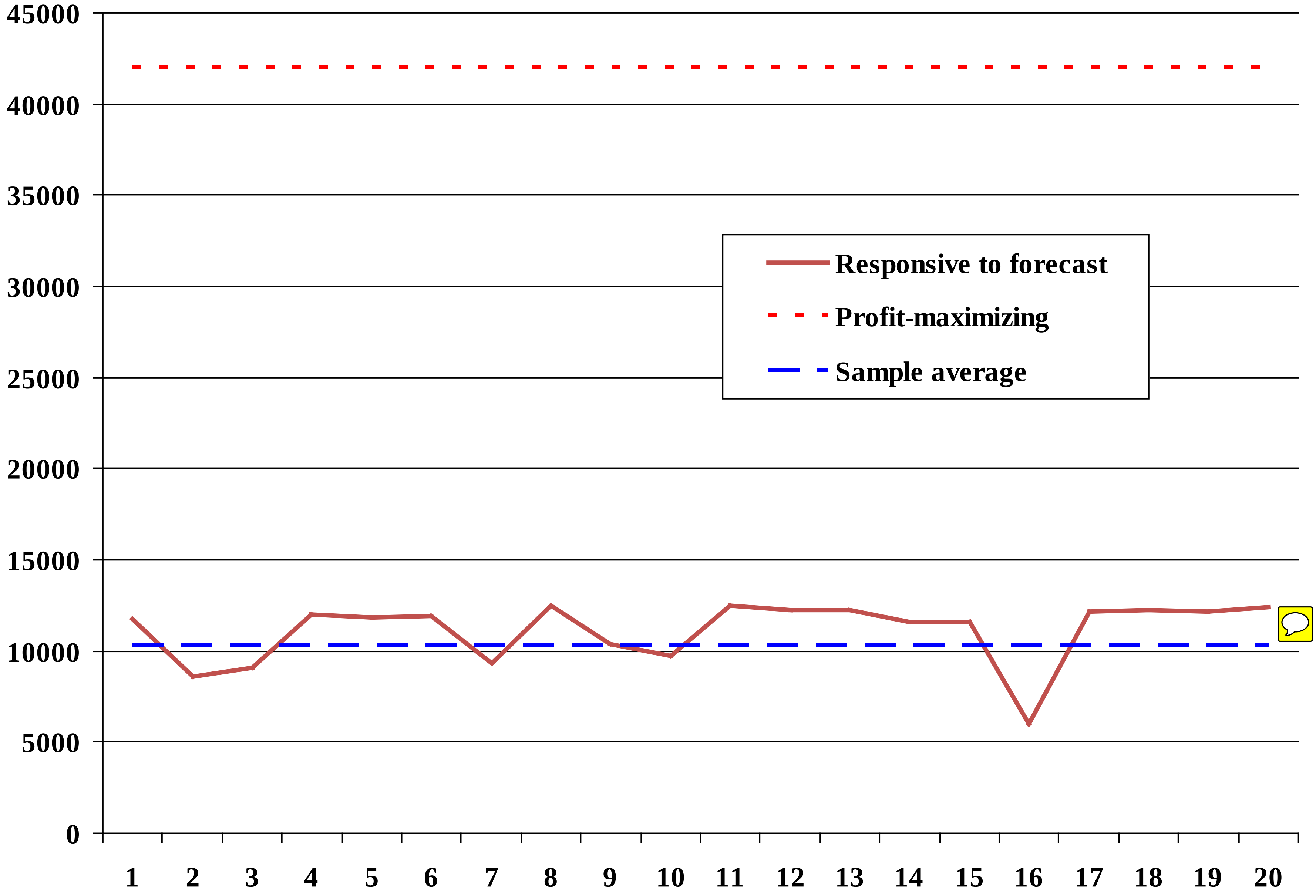


Figure 7. Simulated Profits Over Time

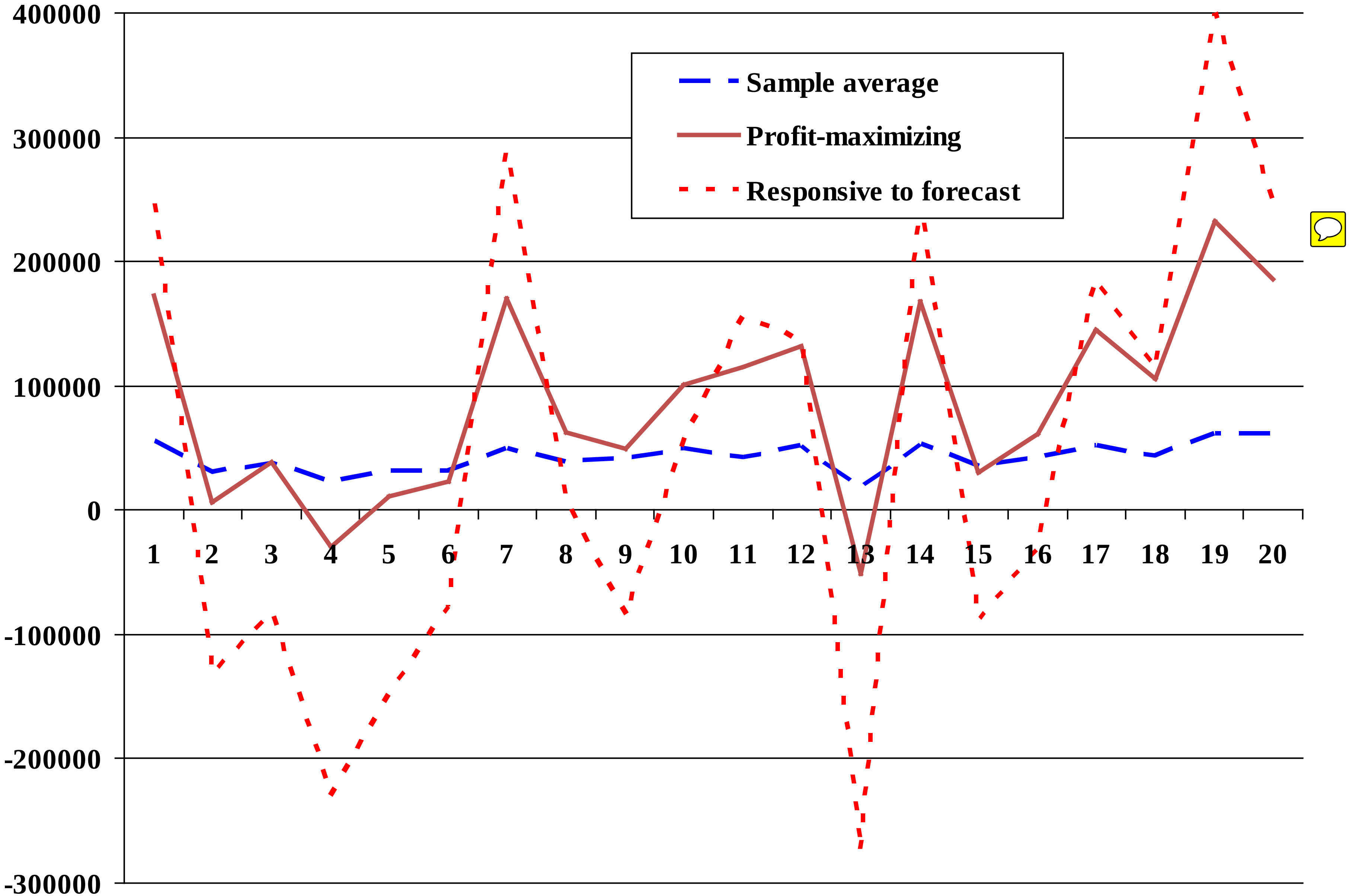


Figure 8. Profits by Forecast Skill and Scenario

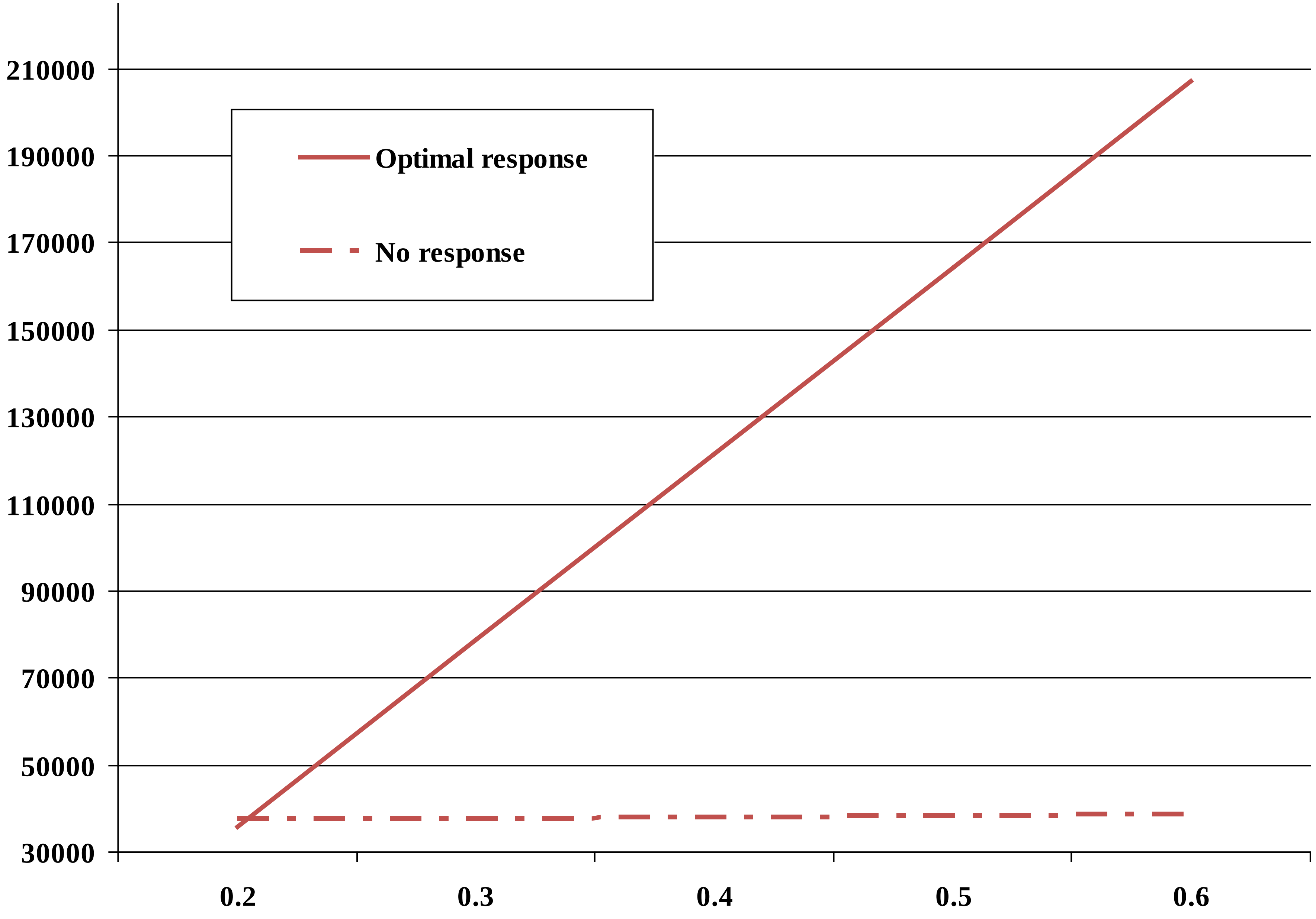


Figure 9. Profits by Forecast Skill and Scenario

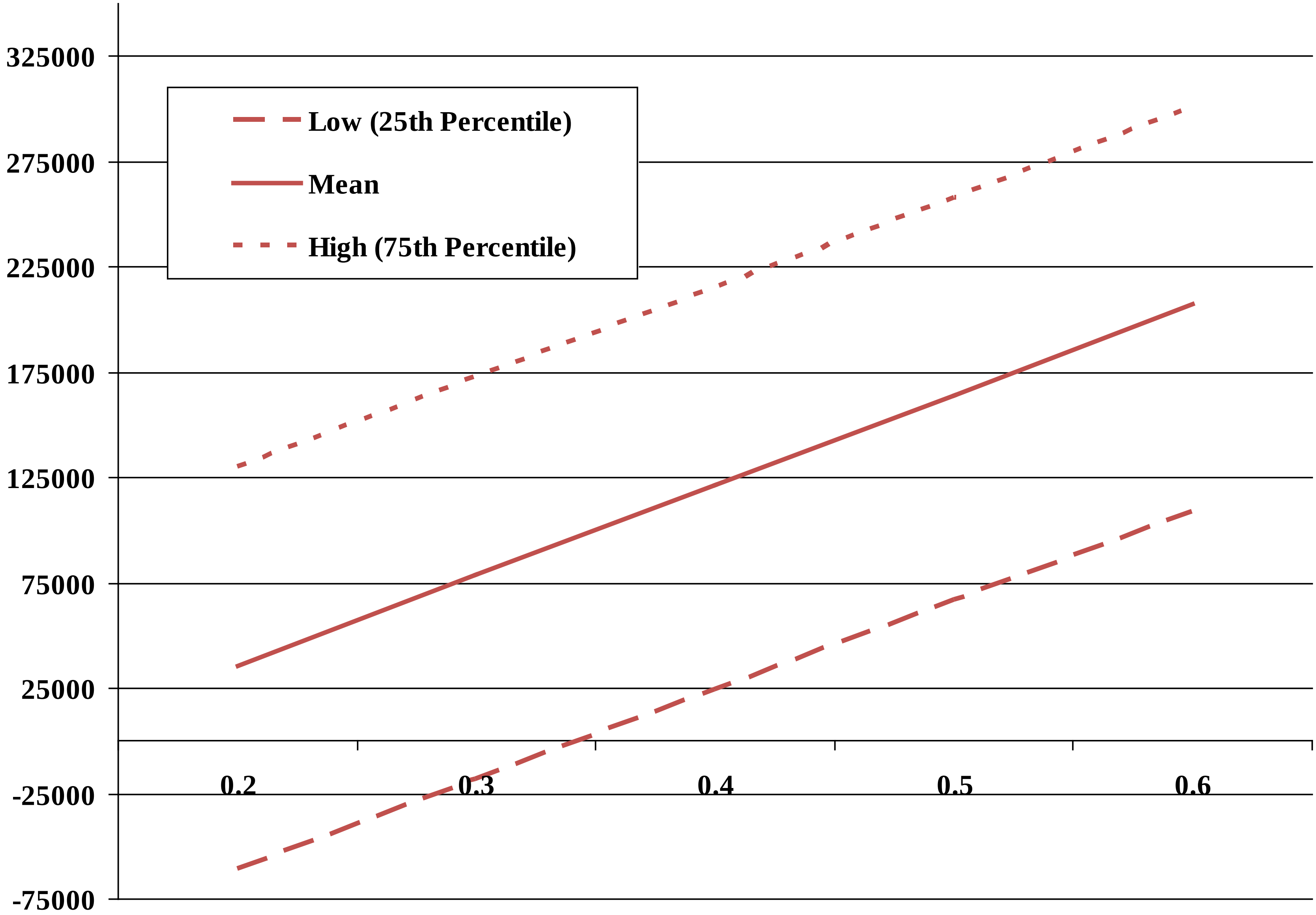


Figure 10. Profit Gain From a 0.1 Increase in Forecast Skill, by Rainfall Realization

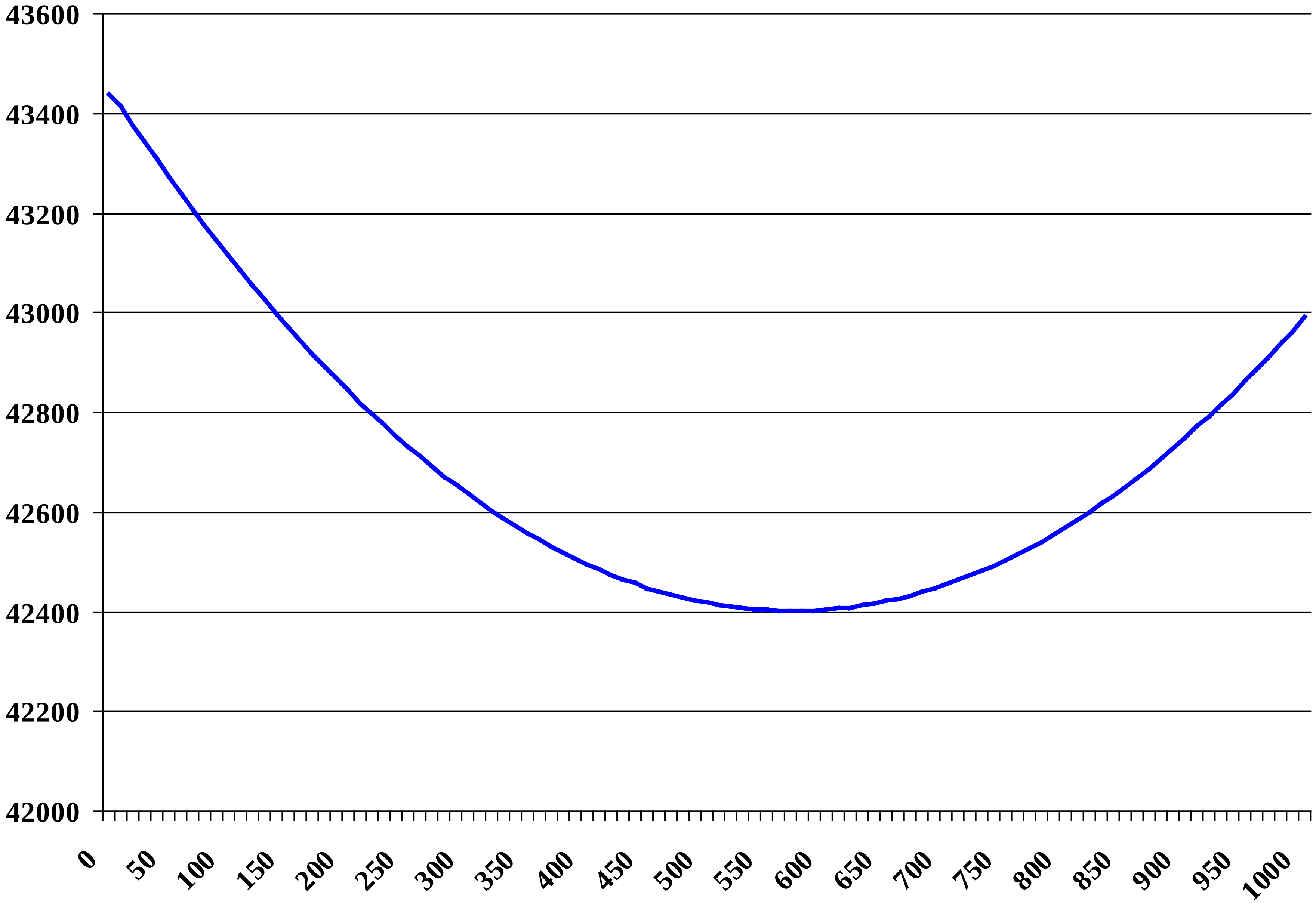
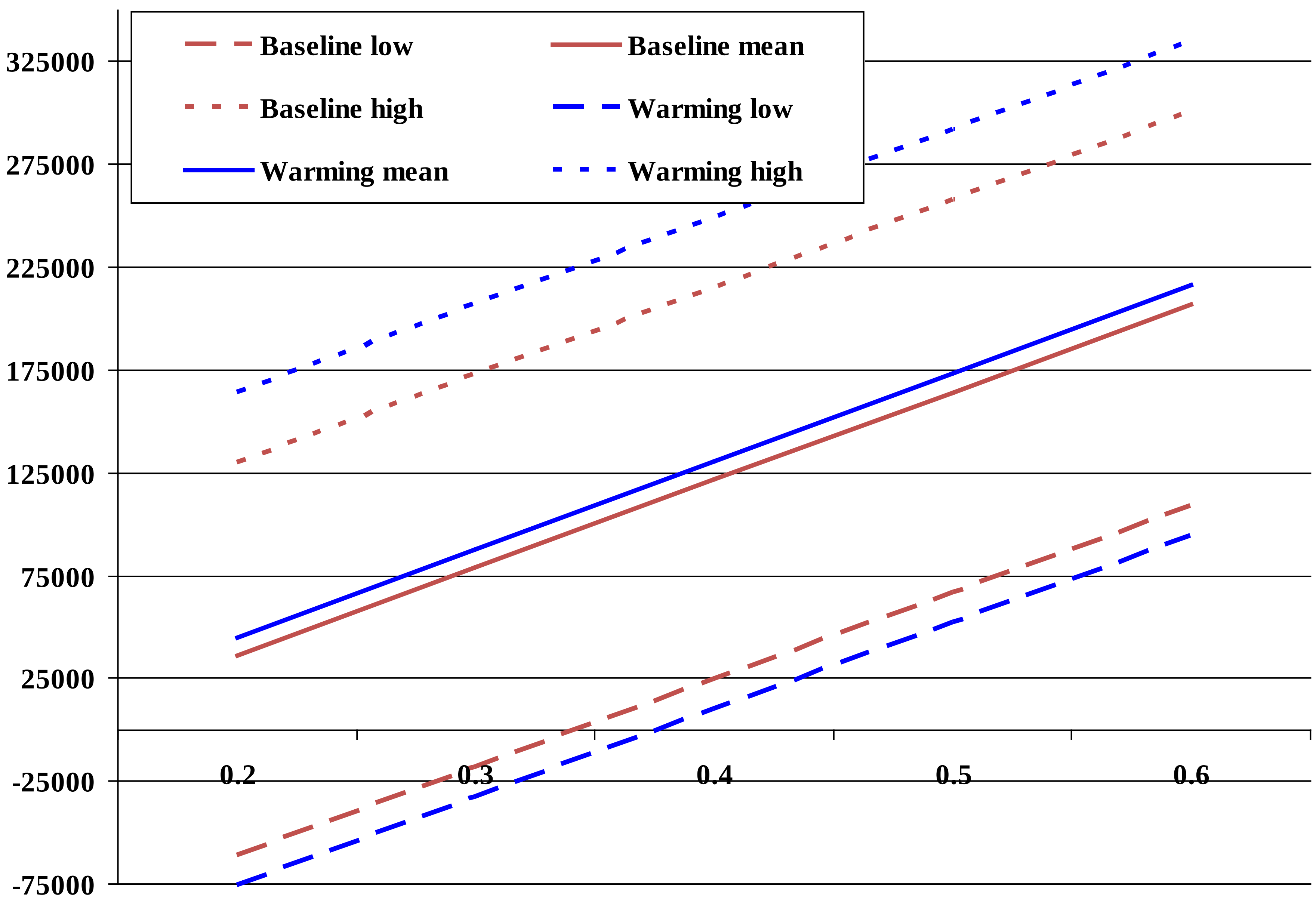


Figure 11. Profits by Forecast Skill and Scenario



Implications for Weather Insurance

- Index products sold at fixed price subject to adverse selection
- Missing market for *forecast insurance*
  - Skilled but imperfect forecasts generate a new risk
  - Insurance paying out after bad weather follows forecast of good would be valuable
    - Three products provide full insurance: conventional index, plus 2 forecast insurance products (e.g. Good after Bad forecast, and Bad after Good forecast)
  - General point: full insurance in a dynamic production environment requires multiple insurance products