Weather risk, crop mix, and wealth in the semi-arid Tropics

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Abstract: This paper estimates the impact of risk aversion on the farm household's choice of crop mix using the ICRISAT panel. To the extent that production risk is uninsured and households are risk averse, the choice of crop mix will deviate from the expected profit maximizing choice. The paper finds that farmer choices of crop mix are affected by weather risk in two of the ICRISAT villages considered here. Since poorer households are less able to smooth consumption ex post, their ex ante choices are further from the expected profit maximizing crop mix. Empirical results support the model of crop choice. Moreover, poorer households allocate land to a mix of crops with lower risk (and lower average profits), as predicted by the model. This likely contributes to the rise in inequality in the villages over the study period.

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I. Introduction

The impact of risk on farm resource allocation in many low-income rural areas is widely recognized. In the absence of complete markets for insuring *ex ante* against adverse shocks to household income, or for adequate mechanisms for *ex-post* consumption smoothing, households are likely to adjust their allocation of household assets (Rosenzweig and Binswanger) and their allocation of household labor between work on-farm and labor supplied in the rural spot labor market (Rose). For many low-income rural households, however, their most important source of income is farm production, and crop production dominates agricultural returns for most of these households in the semi-arid tropics considered below.

An important decision of farm cultivators is the allocation of land under cultivation across different crops. Land accounts for a dominant share of the total asset base (Walker and Ryan, p. 70). Moreover, crops differ widely in terms of yield variability arising from fluctuations in rainfall or other weather variables. If rural households choose less risky crop mixes in order to mitigate against weather uncertainty ex ante, then average farm profits will be smaller, and consumption and welfare accordingly will be lower than would be the case with risk-neutral decision makers. Moreover, the effects of risk likely exacerbates inequality in rural areas, since wealthier households have better access to ex post mechanisms for consumption smoothing than poor households and thus are less likely to choose crop mixes with lower average returns as a hedge against production risk.

The impact of risk on the portfolio of crops by rural households may be an important factor contributing to lower incomes and greater inequality. Moreover, if risk leads rural households to pursue crop portfolios that deviate from the expected profit maximizing choices, straightforward mechanisms for smoothing consumption *ex-post* may have the added benefit of raising average profits from crop production in low-income rural areas.

In fact, the two villages studied here are characterized by a substantial degree of wealth inequality (Table 1). For example, the Gini coefficient for wealth holdings in all the villages was close to 0.5 or greater in 1975. Moreover, inequality as measured by the Gini coefficient appears to have increased substantially during the period covered by the data. By 1983, the Gini coefficient had risen from 0.51 to 0.59 in Aurepalle and from 0.53 to 0.65 in Kanzara. Coefficients of skewness for the villages also indicate a dramatic rise in the skewness of the wealth distribution between 1975 and 1983.

This paper uses data from a sample of rural Indian households collected by the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) to examine the impact of weather risk on the allocation of land across crops with different degrees of susceptibility to weather-related risk. The semi-arid tropics are characterized by a high degree of weather uncertainty, particularly with respect to the timing and conditions of the monsoon, which have significant impacts on crop yields. Previous research has documented the importance of weather uncertainty in affecting the allocation of household asset portfolios (Rosenzweig and Binswanger) and the allocation of household labor between on-farm and off-farm production in the case of India (Kochar, Rose). The ICRISAT data contains detailed information on the timing and extent of the monsoon at the village level, allowing for estimation of the impact of weather uncertainty on crop choice.

The structure of the paper is as follows. The second section describes production in the ICRISAT villages, discusses why risk may affect crop choice, and describes the rising inequality in ICRISAT villages during the study period. The third section lays out a theoretical model of crop choice in which crops exhibit varying degrees of susceptibility to risk. The fourth section discusses empirical results, which suggest that farmer risk aversion influences crop choice substantially in two of the villages. Section V demonstrates that wealthier farmers choose crop mixes characterized by greater profit variance (and higher average profits), which may contribute to greater inequality over time. Section VI concludes.

II. Agricultural Production in the Semi-arid Tropics and the ICRISAT Data

In this paper I use a well-known dataset collected by the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) to study how crop mix is affected by weather uncertainty. Data were collected from forty farmers, thirty of whom were cultivators, in ten different Indian villages representing three distinct regions of India's SAT over the period 1975 to 1984. Data are available from three of the study villages for ten years; three other villages have data available for only six years; data on the other four villages are available for four years. I focus here on two of the original six study villages for which the full time series of data is available.

Agricultural production in the semi-arid tropics is characterized by two main growing seasons. The rainy (kharif) season begins with the onset of the monsoon when soils are water-rich and germination is easy. The post-rainy (rabi) season begins after the monsoon, drawing on moisture stored in the soil after rainy-season crops have been grown. Of the three main ICRISAT study villages for which the longer time series on rainfall is available, kharif-season production dominates in Aurepalle and Kanzara. Kharif production accounted for roughly three-fourths of total area under production in 1983 in Aurepalle and for about 90 percent of total area under production in Kanzara.[1] In contrast, rabi production dominates in the Sholapur villages of Shirapur and Kalman, where kharif crops account for only one-third of area farmed. In these villages, the deep clay soils allow for greater storage of moisture, allowing farmers to cultivate when there is far less uncertainty about crop yields (Walker and Ryan, p.34).

In fact, the kharif season is characterized by a high-degree of uncertainty concerning crop yields and income from crop production when planting takes place. While field preparation for kharif-season production takes place before the onset of the monsoon, most planting activities are triggered with the beginning of rainfall in June or early July. As the monsoon unfolds, planting (and transplanting) occur, fertilizer is applied, fields are weeded, and other production tasks are completed. Farmers must invest considerable resources in planting-season tasks, including purchases of fertilizer and seeds, before the realization of yields or prices is clear. Aurepalle is most susceptible to weather risk, since planting there must begin on a tighter schedule. Aurepalle also exhibits far greater rainfall variability than Kanzara, and is drought prone (Walker and Ryan, p.36).

Weather is a major source of the uncertainty surrounding the returns to crop production in villages dominated by kharif-season cropping, and can be easily summarized by the timing and amount of monsoon rainfall. Crop yields are highly susceptible to variations in the timing and duration of the monsoon. Rosenzweig and Binswanger (1993) found that household profits from crop production are correlated with the monsoon onset date. A model in which weather risk conditions the allocation of land under production to different crops may describe the nature of kharif production, but certainly is less applicable to rabi production. Since rainfall uncertainty is

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[1]Based on author's calculations from ICRISAT data.

largely resolved before rabi production tasks occur, risk aversion should play a smaller role in crop choices. Therefore, I concentrate here on Aurepalle and Kanzara the two villages dominated by kharif production.

Cropping patterns in the ICRISAT villages are complex and characterized by a considerable degree of heterogeneity in crop choice across households within a village and even more so across villages. Table 2 summarizes cropping patterns in Aurepalle and Kanzara at the beginning and end of the study period, e.g. in 1975 and in 1983. The villages were characterized by substantial increases between 1975 and 1983 in the share of total farmland allocated to high-yielding varieties of crops.

In Aurepalle, crop production is dominated by production of traditional sorghum and castor. In 1975 traditional sorghum accounted for about 40 percent of total acres cropped in the village. By 1983 that percentage had fallen to 25. Some of these acres likely went into production of high-yielding varieties of castor, which rose substantially from 1975 to 1983. At the beginning of the sample modern varieties of castor were essentially not grown; by 1983 they accounted for 38 percent of the acres in Aurepalle. Traditional castor varieties fell from 29 percent to 4 percent during the same time frame.

In Kanzara the dominant crop is cotton, which accounted for more than half total acreage in the sample during most of the study period. Sorghum also accounted for roughly 1/5 of acreage in Kanzara at the beginning of the study, with a shift to HYV sorghum by the mid 1980s. Pulses are much less important in Kanzara than in Aurepalle.

III. A Model of Crop Choice

Consider a farm household with a fixed holding of crop land L which is allocated at the beginning of the crop year, before the realization of weather uncertainty to production of n different crops, where α_i is the share of total crop land allocated to the ith crop.[2] The farmer allocates land holdings to maximize utility of consumption. I assume that the farmer's preferences may be summarized by a standard mean-variance utility function $V(\mu_c,\sigma_c)$ where μ_c is expected consumption and σ_c is the standard-deviation of consumption.[3] The farmer maximizes $V(\mu_c,\sigma_c)$, where $V_\mu > 0$ and $V_\sigma < 0$. Meyer shows that the quasiconcavity of $V(\cdot)$ is sufficient to guarantee convexity of preferences, so I assume $V_{\mu\mu} < 0$, $V_{\sigma\sigma} < 0$, and $V_{\mu\mu} V_{\sigma\sigma} - V_{\mu\sigma}^2 > 0$. The farmer can affect the mean and variance of income by choice of crop mix. If $\{\mu_\pi,\sigma_\pi\}$ is the mean and standard deviation of profits from crop production and $\{\mu_\theta,\sigma_\theta\}$ is the mean and standard deviation of the random weather shock, we can write:

$$\mu_\pi = L\ g(\alpha_i)\ \mu_\theta \tag{1}$$

$$\sigma_\pi = L\ \Gamma(\alpha_i)\ \sigma_\theta \tag{2}$$

where L is total land farmed, and constant returns to scale is assumed. The functions $\Gamma(\cdot)$ and $g(\cdot)$ map the distribution of the weather shock θ into the distribution of crop income.

Ignoring other sources of income, the relationship between expected consumption and

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[2]If farm size is endogenous within the crop year, of course, the analysis would be much more complicated. Ignoring decisions concerning inter-cropping and double-cropping, however, it seems reasonable to treat farm size as fixed within crop year t. This is particularly so in the semi-arid tropics where land sales are rare and land rental contracts are likely to be negotiated in advance of planting.

[3]For a discussion of conditions under which the assumption of mean-variance utility function is reasonable, see Rosenzweig and Binswanger 1993.

expected profits is straightforward: $\mu_c = \mu_\pi$. The relationship between the standard deviation in crop profits and the standard deviation in consumption depends on whether farmers have mechanisms available for ex-post consumption smoothing, which could arise from either capital markets (asset sales, as in Rosenzweig and Wolpin), inter-household transfers arising from marriage relationships (Rosenzweig and Stark) or off-farm labor market opportunities (Rose). Farm risk studies such as Just and Pope, and Antle (1987, 1989), assume that $\sigma_c = \sigma_\pi$, while other studies assume perfect ex-post consumption smoothing, e.g. $\sigma_c = 0$ (Paxson). As Rosenzweig and Binswanger assert, the truth is likely somewhere in the middle, with the degree to which farmers are able to smooth consumption ex post related to wealth levels, W, e.g.

$$\sigma_c = \lambda(W)\ \sigma_\pi \tag{3}$$

Substituting (1) through (3) into the utility function V(·), a set of first order conditions for optimal crop choice may be derived as :

$$V_\mu\ g_{\alpha_i} = V_\sigma\ \Gamma_{\alpha_i}\ \sigma_\theta\ \lambda, \quad i=1,2,...n \tag{4}$$

If farmers are risk averse ($V_\sigma \neq 0$) and crops differ in their contribution to profit variability, ($\Gamma_{\alpha_i} \neq 0$), as long as consumption is not perfectly insured against fluctuations in crop-profits ($\lambda \neq 0$) then average profits will be lower than average profits would be with expected profit maximization, which is defined implicitly by $g_{\alpha_i} = 0$.

The first-order conditions in (4) imply several testable hypotheses about the choice of crop mix. First, there should be a positive correlation between a crop's contribution to expected profits and its contribution to profit variability:

$$g_{\alpha_i}/g_{\alpha_j} = \Gamma_{\alpha_i}/\Gamma_{\alpha_j} \tag{5}$$

Moreover, the allocation of land across crops will differ from the allocation that would prevail under expected profit maximization. Crops which have higher expected returns (and thus greater variance in returns) will be under-represented, while those with lower expected returns will be over-represented, compared with the expected- profit-maximizing allocation. The effect of a mean-preserving spread in the standard deviation of the weather shock is to lower the riskiness of the farmer's crop mix Γ and expected profits. But the effect of such an increase in risk will decline with total wealth if either there is declining relative and absolute risk aversion or if $\partial\lambda/\partial W < 0$ (Rosenzweig and Binswanger). Farmers more capable of bearing risk will then also choose crop mixes with higher variance in profits as well as higher average profits from crop production.

IV. Model and Empirical Results

In order to test the relevance of the risk model of crop-choice outlined above, I consider a regression of profits against measures of crop share and rainfall uncertainty. I utilize a normalized quadratic form of the profit function, conditional on the household's allocation choices and on weather uncertainty, θ, for estimation:

$$\pi_{it} = \sum_k \beta_k \alpha_{kit} + 1/2 \sum_j \sum_k \delta_{jk} \alpha_{jit} \alpha_{kit} + \sum_k \gamma_k \alpha_{kit} \theta_t + \gamma_\theta \theta_t + \varepsilon_{it} \tag{6}$$

where α_{kit} refers to the share of crop k in farmer I's crop mix in period t; θ_t is the (village-specific) weather shock to production in year t; and ε_{it} is the household-time specific error term in the regression (discussed below). Parameters to be estimated are given by $\{\beta,\delta,\gamma\}$. Parameters are assumed to be constant across time and households and to reflect only technology. The appropriate measure of weather uncertainty must of course be formalized in order to study the impact of weather uncertainty on household profits. I follow Binswanger and Rosenzweig in using as a measure of rainfall variability the date of the monsoon onset, determined as the date after which there has been at least 20 mm of rain after June 1. [4]

The appropriateness of the model depends on the assumption that all land allocation decisions are made before the weather shock is realized. While this assumption may well be subject to question, the ability of farmers to switch crop choices after the production year begins is certainly constrained in several ways. First, seeds and other variable inputs must be purchased (or withheld from last year's production, if they are traditional varieties) in advance. Moreover, soil preparation differs from crop to crop. Other inputs provided outside the household's own resources likely must be contracted for in advance. Moreover, variable inputs should be allocated in fixed proportion to the land allocation decision and farmers should maximize profits conditional on the land allocation decision and on the realization of weather uncertainty after land allocations have been decided.

One advantage of the generalized quadratic profit function is that it allows us to recover easily the ex-ante riskiness of each households choice of crop mix. The riskiness of each household's land allocation choice, Γ_i, based on (2) and (6) is given by:

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[4]Binswanger and Rosenzweig tested for the significance of several other rainfall variables. They found that the monsoon end date, the average rain per day during the monsoon, and two periods of drought were not statistically significant in determining crop profits in the sample of 10 ICRISAT villages. The frequency of rainfall days during the monsoon was only marginally significant.

$$\Gamma = \sqrt{[\sum_j \gamma_j \alpha_j + \gamma_\theta]^2} \tag{7}$$

The appropriate statistical model for estimation of $\{\beta,\delta,\gamma\}$ in equation (6) depends on the nature of the error term ε_{it}, especially its relationship to the variables included in the regression. If the ε_{it} are correlated with crop mix, then the appropriate estimation technique is household level fixed effects, e.g. fixed effects will give unbiased estimates of the model parameters. On the other hand, if the ε_{it} are not correlated with other variables included in the model, then using a pooled regression will yield more efficient (e.g. lower standard error) parameter estimates. The appropriateness of fixed versus random effects is tested below.[5]

I utilize the detailed production data available in the ICRISAT panel to construct measures of profits from crop production at the household level. Profits from crop production are the difference between the value of all crops grown valued at the village-specific price (whether consumed on-farm or sold) and the opportunity cost of all inputs, where family labor is valued at the village- and gender-specific market wage.

I begin by estimating the normalized profit function using the generalized quadratic form defined in (6). In addition to information on the share of total crop land allocated to each crop and the weather shock, I included total area farmed in order to test for scale effects in the profit regressions. Summary characteristics of household profit regressions at the village level are reported in Table 3 for the two villages. I tested for the presence of fixed effects using the Hausman test and could not reject a null hypothesis of no fixed effects for either village.

[5]Since there are fewer than forty households per village, using village level random effects is not possible in these regressions. There are not enough observations to obtain the “between” coefficient estimates necessary to construct the random effects estimates.

Therefore, I report results based on pooled regressions; the standard errors are corrected for possible effects of village level clustering which would otherwise cause the estimated standard errors to be biased downward (Moulton).

The model did a somewhat better job of capturing variation in household profits for Aurepalle (column 1), and the R-squared was 0.70. An F-test for significance of the weather terms was significant at less than the one percent level, indicating that the monsoon onset date is important in determining household profits. A test for the joint significance of the share interaction terms in (6), e.g. for the δ_{ij} where $I \neq j$, suggested that the share interactions are statistically significant at the one percent level. The coefficient on total area farmed was not statistically significant, indicating that scale effects are mild in Aurepalle. Since the availability of irrigation is likely to be important in determining cropping patterns, I included the share of irrigated land held by the household in the regressions as well. The coefficient was not statistically significant at even the 10 percent level.

Estimation results for Kanzara are reported in column 2 of Table 3. The R-squared in the regression was only 0.39, indicating a somewhat weaker fit to the data. The t-statistic on total area farmed was not significant, indicating no evidence of scale effects in crop production. Variables measuring the effect of monsoon onset were jointly significant at the one percent level, as were the variables on the share interaction terms, δ_{ij}.

An important result of the model of crop choice here is a positive correlation between the effect of a crop on mean profits and its effect on the riskiness of farm profits (profit variance), as given in equation (5) above. Tables 4 and 5 give estimates of the effects of different crops on mean profit and profit-variance in the villages. In each case, results are reported relative to the mean and risk effects of vegetable crops, to allow for easier interpretation. Results for Aurepalle conform well with the predictions of the model from equation (5). For most of the crops, the relationship between the effect of average profits and the effect on the profit variance has the same sign. Moreover, the simple correlation coefficient between the measures in column (1) and column (3) is 0.86. Production of HYV paddy is associated with sharply higher average profits per acre, and with a higher variance in total profits as well. Traditional castor and traditional paddy, as well as HYV paddy are all associated with lower average profits. Traditional sorghum, which accounts for 38 percent of total cropland is associated with higher average profits, but a lower profit variance, at odds with the prediction of the model. Results for Kanzara, Table 5, also conform well with the predictions of the model. The correlation between profit mean and variance effects is 0.60 in Kanzara, somewhat weaker than for Aurepalle. HYV varieties of cotton are associated with sharply higher average profits and greater risk in profits as well, as might be expected.

V. Wealth and the portfolio of crops

The structure of the model above suggests that if farmers are better able to smooth consumption ex post in the face of a negative weather shock, they are more likely to choose a riskier mix of crops. Of course, the presence of perfect credit (or insurance) markets would be one such means of ex post smoothing. In the absence of perfect credit or insurance markets however, wealthier households are likely to have greater ability for smoothing consumption ex post, suggesting that wealthier households are likely to choose crops with higher average profits as well as higher profit variance. Such a finding has important implications for income distribution. If wealthier families earn higher average profits from crop production, then income inequality is likely to become greater over time. Moreover, as new crops (or HYV varieties) with higher average profits and higher profit variance are introduced, the problem will worsen.

Figures 1 and 2 show the relationship between profit variance and total (real) assets for Aurepalle and Kanzara. The graphs suggest that there is a positive correlation between total household wealth and the level of risk associated with the household's crop mix. To test this result I regressed the household level measures of portfolio riskiness, Γ_i, constructed using the form in equation (7) and empirical estimates of $\{\beta, \delta, \gamma\}$, against the level of total household wealth. While total wealth holdings will not in general be independent of households preference mappings for risk, implying that estimates of the effect of wealth on the riskiness of crop mix would be potentially biased, the panel structure of the ICRISAT data allows me to sweep out any differences that are fixed over time by the use of fixed effects estimators.

The results reported in Table 6 suggest that indeed wealthier farmers choose mixes of crops with higher degrees of riskiness, and higher average returns. For Aurepalle, I reject a null hypothesis of no farmer-specific fixed effects at the five percent level, suggesting that heterogeneity in risk preferences present in the data would bias the random effects estimates. Household wealth explains nearly one-quarter of the overall variability in Γ_i in Aurepalle. The coefficient on total real wealth is positive and statistically significant at the five percent level, while the square of wealth is negative (but significant at only the 20 percent level), indicating some nonlinearity in the response of crop mix to wealth. For Kanzara, I can reject the null of no fixed effects at only the twenty percent level. Nonetheless, I report the fixed effects estimates since they are free from any bias arising from household differences in risk aversion. Total real household wealth explains only about a fourth of the variation in Γ_i in Kanzara. The coefficient on total real wealth is positive, and statistically significant at the five percent level; the square of total wealth is negative, but not statistically significant.

VI. Conclusion

I find that risk aversion may play an important role in determining crop choice in Aurepalle and Kanzara. There is a positive correlation between a crop's effect on mean profits and its effect on profit variance in both villages. Likewise, I find that the variance in crop profits is positively associated with higher levels of real wealth, indicating that the ability to smooth consumption ex post leads farmers to choose a mix of crops with higher average profits, exacerbating income and wealth inequality over time, especially with the introduction of riskier HYVs. A further direction for research is to determine the extent to which crop choice interacts with labor and land market imperfections in the study villages.

Table 1

Inequality in the ICRISAT Villages

Summary measure of the Distribution of Real Assets

1975 and 1983

	Aurepalle		Kanzara	
	1975	1983	1975	1983
Interquartile Range	10784	17629	17631	9312
Gini Co-coefficient	0.51	0.59	0.53	0.65
Ratio of 95th percentile to 5th percentile	49.1	61.1	30.8	187.8
Coefficient of Skewness	1.19	3.30	1.71	2.37

Table 2

Cropping Patterns in ICRISAT Villages
By main crop (inter-cropping is not considered)

1975 and 1983

	Aurepalle		Kanzara	
	1975	1983	1975	1983
Vegetables	.05	.01	.00	.02
Pulses	.02	.03	.03	.06
Traditional Sorghum	.41	.24	.19	.11
HYV Sorghum			.07	.20
Traditional Paddy	.06	.02		
HYV Paddy	.11	.16		
Castor	.29	.05		
HYV Castor	0	.38		
Groundnuts			.10	.07
HYV Wheat			.03	.02
Traditional Cotton			.51	.51
HYV Cotton			.02	.01

Table 3

Summary of Profit Regressions
Dependent Variable: Profits per acre

Pooled regressions, robust standard errors corrected for village clustering

	Aurepalle (1)	Kanzara (2)
Share of irrigated land	194.6	168.4
(t-statistic)	(0.90)	(0.63)
Total area farmed	-1.15	0.35
(t-statistic)	(-0.77)	(0.36)
F-test for significance of rainfall variables (p-value)	7.61 (0.00)	3.16 (0.01)
F- test for land share interaction terms (δ_{ij}) (p-value)	3.42 (0.00)	404.0 (0.00)
Hausman χ^2test for fixed effects (p-value)	13.5 (1.00)	21.7 (1.00)
N	292	290
R^2	0.70	0.39

* indicates significance at the 10 percent level
** indicates significance at the 5 percent level
*** indicates significance at the 1 percent level

Table 4

Marginal Effects on expected profits and on profit variance in Aurepalle
(Relative to vegetable crops, evaluated at sample means)

	Sample Mean	$\partial\pi / \partial\alpha_i$	$\partial\Gamma^2/\partial\alpha_i$
Pulses	.03	-3.58	-1.95
Traditional Sorghum	.38	2.18	-1.17
Traditional Paddy	.03	-3.18	0.09
Improved Paddy	.08	10.70	3.60
Traditional Castor	.29	-2.99	-0.97
Improved Castor	.12	-2.01	-1.07
Correlation coefficient between $\partial\pi / \partial\alpha_i$ and $\partial\Gamma^2/\partial\alpha_i$		0.86	

Table 5

Marginal Effects on expected profits and on profit variance in Kanzara
(Relative to vegetable crops, evaluated at sample means)

	Sample Mean	$\partial\pi / \partial\alpha_i$	$\partial\Gamma^2/\partial\alpha_i$
Pulses	.05	0.09	0.10
Traditional Sorghum	.13	-0.19	0.13
Improved Sorghum	.15	0.46	0.12
Improved Wheat	.02	-0.73	0.20
Traditional Cotton	.57	0.30	0.12
Improved Cotton	.01	2.01	0.54
Groundnuts	.05	0.26	0.18
Correlation coefficient between $\partial\pi / \partial\alpha_i$ and $\partial\Gamma^2/\partial\alpha_i$		0.60	

Table 6

Determinants of Crop Mix Riskiness (Γ_i)

Household fixed effects estimates

	Aurepalle (1)	Kanzara (2)
Household real wealth ($\times 10^{-3}$)	1.41** (2.04)	0.68** (2.10)
Household real wealth squared ($\times 10^{-9}$)	-5.75 (-1.31)	-2.15 (-0.71)
Regression R-squared	0.24	0.28
Hausman test for fixed effects (p-value)	6.68 (0.04)	3.31 (0.19)

t-statistics in parentheses
* indicates significance at the 10 percent level
** indicates significance at the 5 percent level
*** indicates significance at the 1 percent level

Figure 1

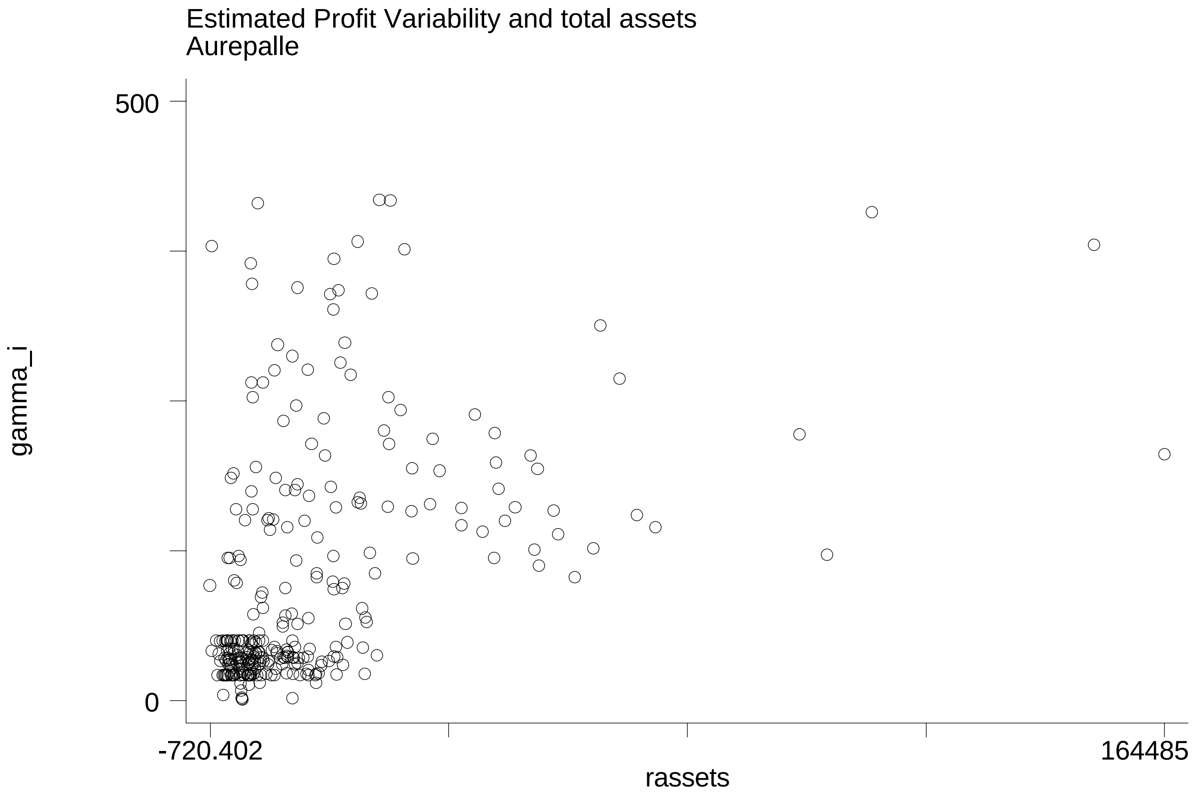
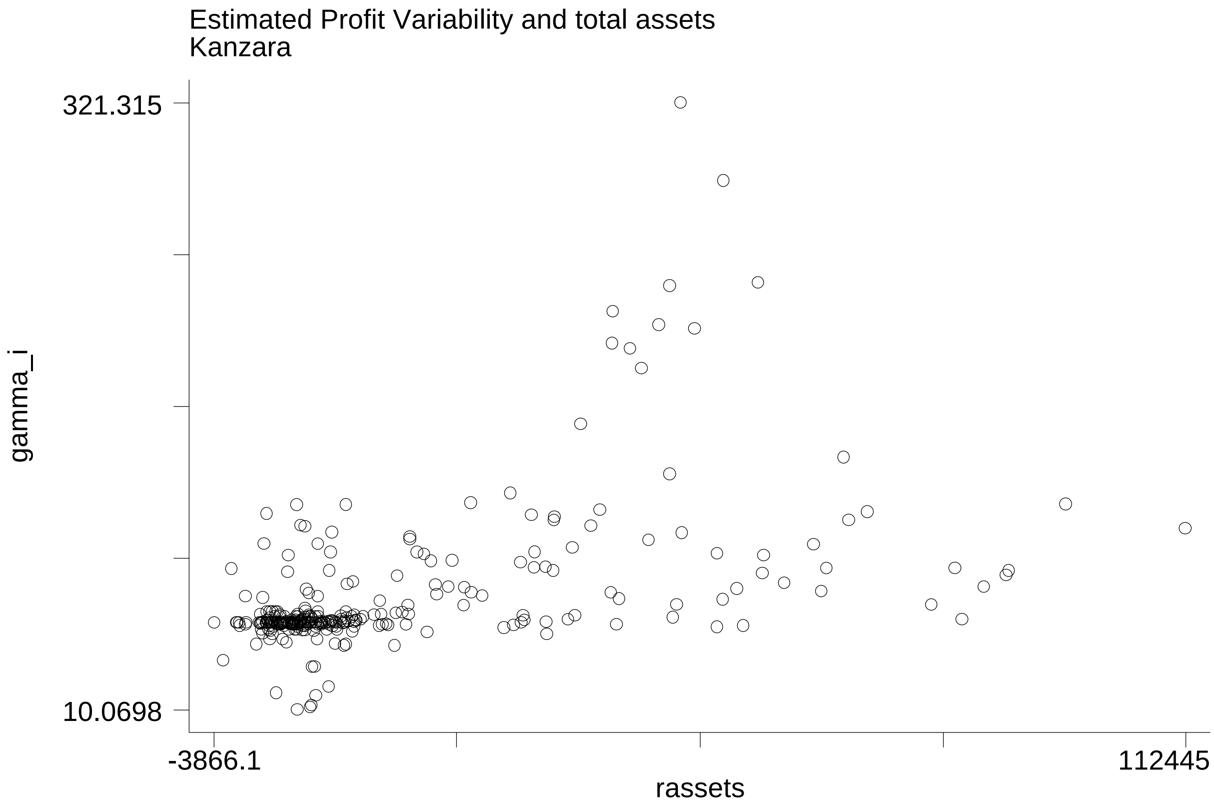

Estimated Profit Variability and total assets
Aurepalle
500
0
gamma_i
-720.402
164485
rassets

Figure 2


Estimated Profit Variability and total assets
Kanzara
321.315
10.0698
gamma_i
-3866.1
112445
rassets

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