Fertilizer Use, Risk, and Off-farm Labor Markets In the Semi-Arid Tropics of India

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Russell L. Lamb

Assistant Professor
Department of Agricultural and Resource Economics
North Carolina State University
Campus Box 8109
Raleigh, NC 27695-8109

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Abstract: The opportunity to work in the off-farm labor market allows farmers to smooth consumption in the face of a negative weather shock. This allows farmers to make production choices that have higher average returns, and greater risk. I develop a two-period dynamic programming model to explain the relationship between fertilizer demand and off-farm labor markets for a risk-averse farmer. I use a well-known sample of farmers in the semi-arid tropics of India to test the model. I show that fertilizer demand increases with the depth of the off-farm labor market. Controlling for exogenous weather risk, farmers use more fertilizer the lower the unemployment rate and the higher the share of nonagricultural work in total off-farm labor. The results have important policy implications, suggesting that labor markets and farm production are complementary in risky production environments.

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I. Introduction

The primary means of "getting agriculture moving" and raising rural incomes in developing countries has been the diffusion of new production techniques, especially high-yielding varieties of seeds, chemical fertilizers, and pesticides. A major impediment to the adoption of such modern inputs is the well-documented risk aversion on the part of rural decision makers in developing countries (Moscardi and de Jainvry , Binswanger (1980, 1981) and Antle (1987, 1989)). Risk-averse farmers will try to mitigate risk ex-ante[1] and smooth consumption ex-post.

A number of authors have documented the role of ex-post consumption smoothing and its effect on various aspects of rural household behavior. Rosenzweig and Wolpin show that sales of farm assets (e.g. bullocks) are used to smooth consumption by farmers whose income is lowered by a negative production shock. Rose shows that ex-post off-farm labor supply responds to weather shocks. Paxon shows that household level consumption is largely explained by village-level consumption patterns, indicating that idiosyncratic income shocks are smoothed across household within the village in Thailand. Rosenzweig shows that inter-village transfers of wealth by family members are used to smooth consumption across villages.

To the extent that consumption risk is imperfectly insured, farmers' ex-ante choices will be affected by risk aversion. For example, Rosenzweig and Stark show that inter-village transfers may help explain the prominence of patriarchal exogamy in India and accompanying patterns of migration. Rosenzweig and Binswanger show that farmers in more risky areas deviate more from the optimal portfolio of assets, and that this deviation is worse among poorer farmers than wealthier ones. Indeed, risk aversion has been argued to play an important role in inhibiting the

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[1]Ex-ante refers to the period before (ex-ante) the realization of the weather shock, and ex-post the period after the shock is realized.

spread of modern inputs (Feder, Just and Zilberman). Moreover, the risk-increasing role of modern inputs exacerbates the effect of risk aversion on production choices. Rosenzweig and Shaban shows that farmers use share-tenancy contracts to spread the risk of new seeds when they are first introduced and their cultivation properties are still uncertain. To the extent that farmers choose traditional inputs over modern inputs in order to lower risk ex-ante, any mechanism that allows farmers to smooth consumption ex-post will raise the use of modern inputs and increase farmer productivity. Since poorer farmers are likely more risk averse than wealthy farmers, their choice will be affected more by increased opportunities for ex-post consumption smoothing.

One such mechanism for ex-post consumption smoothing is the use of off-farm labor supply in the daily wage labor market. Kochar finds that household earnings from day labor respond positively to negative (idiosyncratic) production shocks using the same data set used here. Rose finds that second-period labor responds negatively to negative production shocks as well using a different set of data on Indian households.

In this paper I show that farm households use off-farm labor supply to mitigate the effects of production shocks ex-post in a dynamic production environment, and this leads to more efficient ex-ante production choices in the presence of production risk, in particular greater use of chemical fertilizer. The organization of the paper is as follows. In Section II, I describe the production environment and the structure of off-farm labor markets in the ICRISAT villages. In Section III, I develop a two-period model of a risk-averse, expected utility maximizing farmer who chooses fertilizer in the first period and off-farm labor supply in the second period. In Section IV, I present estimates of fertilizer demand which show that fertilizer demand increases as the off-farm labor market deepens. Section V concludes.

II. Production in the Semi-Arid Tropics of India and the ICRISAT Panel

Previous research has found that the supply of harvest-season labor in the off-farm labor market is an important method for smoothing consumption in the presence of negative shocks to farm production. If that is so, then the efficiency of ex-ante choices will be improved, in particular the degree of inefficiency arising because of risk aversion. I use a well-known dataset collected by the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) to study the effect of labor market structure on fertilizer demand d by risk-averse farm households facing substantial, weather-related production risk.

Data were collected by ICRISAT from forty farmers, thirty of whom were cultivators and ten of whom were landless laborers, 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; date on the other four villages are available for two years. I focus on the three main study villages of Aurepalle, Shirapur, and Kanzara plus Boriya and Rampura, since data is available for these villages on both the structure of the off-farm labor market and the intensity of fertilizer use.

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, which is somewhat less important in overall agriculture, begins after the monsoon, drawing on moisture stored in the soil after rainy-season crops have been grown.

Kharif-season production dominates in most of the ICRISAT villages; an exception is Shirapur, where rabi-season crops are more important. I am interested in the interplay of risk aversion and off-farm labor markets. Since rabi production occurs after the uncertainty surrounding rainfall has been resolved, risk is unlikely to play a significant role in affecting fertilizer use for rabi season crops. Moreover, the model developed below more adequately describes kharif production. Therefore, I ignore rabi-season fertilizer use in the estimation that follows.

Weather is a major source of the uncertainty surrounding the production environment and can be summarized by the timing and amount of rainfall. Crop yields are highly susceptible to variations in the timing and duration of the monsoon. Rosenzweig and Binswanger found that household profits from crop production are correlated with the monsoon onset date and Skoufias found total agricultural output to be strongly dependent on the monsoon onset as well. Moreover, Barah and Binswanger find that for unirrigated areas of the semi-arid tropics of India, yield variability contributed more than price variability to fluctuations in gross-crop revenue, indicating the importance of weather-induced yield fluctuations in household income risk.

The extent of fertilizer use varies widely across the ICRISAT villages and across time. Figures 1.1 through 1.3 shows the extent of fertilizer use for Aurepalle, Shirapur, and Kanzara, from 1975 through 1983. For both Aurepalle and Kanzara the extent of fertilizer use increased fairly substantially from the beginning of the ICRISAT study to the end. In the mid-70s only 20 percent of the farmers in Aurepalle and ½ of the farmers in Kanzara used fertilizer on their fields. By 1984, almost 3/4 of the farmers in Aurepalle and over 90 percent of the farmers in Kanzara used some chemical fertilizer. Fertilizer use is much lower in Shirapur and did not increase appreciably during the study period.

The kharif season is characterized by a high-degree of uncertainty concerning the effectiveness of fertilizer application. While field preparation for kharif production takes place before the monsoon onset, 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. The vast majority of fertilizer applied to kharif season crops occurs during the monsoon; little fertilization takes place after the end of the monsoon in most villages. In fact, in both Aurepalle and Kanzara over 95 percent of all fertilizer used during the kharif season is applied either before the monsoon onset or between the monsoon onset and end (Figure 2). Farmers must invest considerable resources in fertilizer application before it is clear whether fertilizer use will be effective or not.

The ICRISAT data set is well-suited to considering the effect of off-farm labor markets on ex-ante decision making because it contains detailed information on the timing of production and labor market activities by the household, which allows ex-ante information set to be identified and the depth of the labor market in the planting period to be measured.

Most rural households in the semi-arid tropics engage in substantial labor activities off their own farms. Off-farm labor supply is an important source of household income and labor markets are well developed and complex. Although men and women contribute about equally to crop labor, women dominate in the off-farm labor market. Off-farm labor supply varies by gender across the crop production cycle, due to custom. While harvesting and threshing are undertaken by both men and women, most other tasks are gender-specific (Walker and Ryan, p.110). Men concentrate on nine specific production tasks, four of which involve the use of bullock power, reflecting the fact that women are prevented by custom from touching the plow (Walker and

Ryan, p.125).[2] The result of this is substantial labor market segmentation by gender in the study villages. In turn, there is little correlation between male and female wages across production years in four of the six villages, and in none of the villages do male and female wages move together within the crop year (Walker and Ryan, p. 124).

Segmentation of labor market tasks shows up in the share of labor supply accounted for by pre-harvest and harvest labor, by gender. Pre-harvest labor accounts for between 50 and 75 percent of male (off-farm) labor supply during the year for the three villages (averaged across all years in the sample). In contrast, pre-harvest labor supply accounts for almost 50 percent of the total for females in Kanzara, but is closer to 25 percent in both Aurepalle and Shirapur (Figure 3). The dominance of second-period labor in female off-farm labor supply likely arises because of the dominance of harvest tasks in female agricultural work.

If the supply of harvest-season labor in the off-farm labor market is an important tool for smoothing consumption, there should be significant interactions between fertilizer use and off-farm labor supply. A natural first step is to look at whether the availability of off-farm employment opportunities raises fertilizer use. Since farmers must form expectations about the harvest-season labor market at planting time, it is planting-period labor market conditions that should affect fertilizer use. Ignoring the role of off-farm labor in ex-post consumption smoothing, higher levels of involuntary unemployment would cause farmers to allocate more labor to on-farm production, since involuntary unemployment acts like a tax on the market wage. Since on-farm labor and fertilizer are widely viewed as complementary in production, this would boost fertilizer use. On the other hand, if off-farm labor markets are a tool for consumption smoothing then

[2] Nursery-bed raising, planting, transplanting, thinning and weeding are gender-specific to women.

lower levels of involuntary unemployment in the off-farm labor market would make it easier for farmers to smooth consumption ex post in the face of a negative production shock. In this case, lower levels of unemployment in the labor market should raise fertilizer use.

In fact, there is a substantial *negative* correlation between the planting season unemployment rate (for both males and females) and the share of farmers using chemical fertilizers in the three villages (Figure 4). This suggests that in fact farmers may use the off-farm labor market as a consumption-smoothing mechanism in case of a crop failure.

III. Theoretical Model

I develop a formal model relating the depth of the off-farm labor market to fertilizer use. Consider an expected-utility-maximizing farmer who produces a single crop over a two-period (intra-year) crop cycle. Assume that the farmer's preferences are characterized by a strictly concave utility function U(I), where I is total income, U' > 0, and U"< 0. All consumption takes place in period 2.

The two distinct production periods are identified by a village-level random production shock θ_k where k indexes villages. The shock, which is fully known at the beginning of the second period, has mean $\bar{\theta}_k$, and a purely random component, $\tilde{\theta}_k$, which the farmer cannot forecast using information available in the first period. The random shock $\tilde{\theta}_k$ is assumed to be i.i.d. across time with zero mean and finite variance, σ_k^2; rainfall uncertainty varies across villages. The production shock may be thought of as village-level weather patterns, which are critical in determining farm profits in the semi-arid tropics considered below. More specifically, while the monsoon onset is well known before most production activities get underway, information about the length of the monsoon, the total amount of rainfall, and the distribution of rainfall during the monsoon (frequency of rainfall days, etc) is not known.

In the first period, the farmer chooses the quantity of the variable input, which may be fertilizer or pesticide, for example. In the second period the farmer allocates household labor between labor used in crop production (l) and off-farm labor supply (L).[3] Each household is endowed with a fixed quantity of labor resource, $\bar{L}$, and the household's labor constraint is given by:

$$L + l = \bar{L}. \tag{1}$$

Let Q denote output. The production technology is given in (2):

$$Q = [\bar{\theta}_k + (1-\gamma)\tilde{\theta}_k]f(X,\bar{L}-L) \tag{2}$$

where X is variable input; γ is a parameter that affects the farmer's ability to cope with rainfall uncertainty, which might measure the share of irrigated land; $\bar{L}-L$ is labor used in crop production, substituting in the constraint in (1); $f(X,\bar{L}-L)$ has the properties of a neoclassical production function: $f_x>0$, $f_l>0$, $f_{ll}<0$, $f_{xx}<0$, $f_{xl}>0$, and $f_{ll}f_{xx} - f_{xl}^2 > 0$. Equation (2) decomposes the effect of weather into its mean and random components. The effect of $\tilde{\theta}_k$, on output depends inversely on γ. For example, weather uncertainty is less important for output the greater the level of irrigation.

Farmers may also sell their labor in the off-farm labor market at a wage rate w_k where k

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[3]There is a labor allocation decision in the first period as well. Including the first-period labor allocation decision greatly complicates the analytics of the model, since it increases the dimension to 3 inputs. To the extent that labor use is proportional to fertilizer use in the first-period, then omitting the labor choice from the first-period will not bias the results.

refers to the farmer's village. The weather shock affects the wage paid in the off-farm labor market, $w_k = \bar{w}_k + (1-d_k)\tilde{\theta}_k$. For a given level of d in the local labor market, positive (negative) weather shocks increase (decrease) the demand for labor and thus the wage. The expected wage in village k is $\bar{w}_k$, and the variance of the village wage is given by $\sigma_k^2\ (1-d_k)^2$, so that the effect of the weather shock on the variance of the village wage depends inversely on the depth of the village labor market, d_k. A useful interpretation of the parameter d is d = (1-UR) where UR is the village level unemployment rate.

The farmer's total profits from on-farm production and off-farm labor supply are:

$$\pi = [\bar{\theta}_k + (1-\gamma)\ \tilde{\theta}_k]\ f(X,\bar{L}-L) - qX + (\bar{w}_k + (1-d_k)\tilde{\theta}_k)L \tag{3}$$

where input price is denoted by q and output price is normalized to one.

The farmer uses the standard dynamic programming algorithm to solve the maximization problem (Intrilligator, 1971). He first solves the second period problem by choosing the optimal allocation of labor between farm-production and off-farm labor supply in the second period, conditional on his choice of fertilizer in the first period, and the realization of production shock. Since there is no uncertainty, the farmer's problem is to maximize profits. The first-order condition for the second-period maximization problem is given in (4):

$$[\bar{w}_k + (1-d)\tilde{\theta}_k^*] - [\bar{\theta}_k+(1-\gamma)\tilde{\theta}_k^*]f_l(X^*,\bar{L}-L) = 0 \tag{4}$$

where X^* is the optimal level of fertilizer from the first-period maximization problem and $\tilde{\theta}_k^*$ is the realization of the random shock. The second order condition for maximization requires $(\bar{\theta}_k+(1-\gamma)\tilde{\theta}_k^*)f_{ll}<0$, which holds if and only if $(\bar{\theta}_k+(1-\gamma)\tilde{\theta}_k^*)>0$; this is a regularity condition ensuring that total output is positive.

Totally differentiating the first-order condition, we can derive the comparative statics for second-period labor supply. Increases in the average wage increase off-farm labor supply, ceteris paribus (conditional on the actual θ^* and X^*):

$$\partial L/\partial \bar{w}_k = -1/[\bar{\theta}_k + (1-\gamma)\tilde{\theta}_k^*]f_{11} > 0 \tag{5}$$

by the second order conditions. Evaluated at the mean of the weather shock, $\tilde{\theta}_k = 0$, the weather uncertainty has no effect on the slope of the labor supply curve.

The effect of the production shock on second-period labor supply is:

$$\partial L/\partial \tilde{\theta}_k^* = \frac{[(1-\gamma)f_1 - (1-d_k)]}{[\bar{\theta}_k + (1-\gamma)\tilde{\theta}_k^*]f_{11}} . \tag{6}$$

If better rainfall raises the marginal productivity of labor by more than it raises the off-farm wage, e.g. $(1-\gamma)f_1 > (1-d_k)$, then $\partial L/\partial \tilde{\theta}^* < 0$ holds, and farmers supply less labor off-farm the greater the production shock. In the extreme case in which d_k=1, e.g. the village labor market is fully diversified, then better weather always lowers off-farm labor supply since the wage is independent of the weather shock, e.g. $\partial L/\partial \tilde{\theta}_k^* < 0$. The key relationship is that between the effect of the random weather shock on the marginal productivity of farm production labor (through γ) and its effect on the wage in the village labor market (through d_k). There are good reasons to think that the weather-shock affects on-farm production labor more than the wage in the village market. Even in the village economies, labor has uses outside agriculture. Moreover, labor is portable, so the impact on the wage in the village should be limited by the costs of moving labor to another village.

Off-farm labor also responds to the quantity of fertilizer used by the farmer in the first period, e.g. $\partial L/\partial X^* = f_{1x}/f_{11}$. If fertilizer use raises the marginal productivity of labor, then $\partial L/\partial X^* < 0$. In the case of negative production shocks, off-farm labor supply is higher the greater is the depth of the local labor market, d_k:

$$\partial L/\partial d_k = \tilde{\theta}_k^*/[\bar{\theta}_k + (1-\gamma)\tilde{\theta}_k]f_{11} > 0 \text{ for } \theta_k^* < 0. \quad (7)$$

Likewise, in the presence of negative production shocks, labor supplied off-farm is lower the higher the share of irrigated land:

$$\partial L/\partial \gamma = -\tilde{\theta}_k^* f_l/[\bar{\theta}_k + (1-\gamma)\tilde{\theta}_k]f_{11} < 0. \quad (8)$$

Irrigation is an important tool available to help farmers mitigate the effects of negative rainfall shocks. The effect of γ on the response of second period labor supply to the rainfall shock is given by:

$$\partial^2 L/\partial\tilde{\theta}_k^*\partial\gamma = \frac{-f_l[\bar{\theta}_k + (1-\gamma)\tilde{\theta}_k^*]f_{11} + [(1-\gamma)f_l-(1-d_k)][\tilde{\theta}_k^* f_{11}]}{[\bar{\theta}_k + (1-\gamma)\tilde{\theta}_k^*]^2 f_{11}^2} \quad (9)$$

which is always positive for negative production shocks, e.g. $\partial^2 L/\partial\theta_k^*\partial\gamma > 0$ if $\tilde{\theta}_k < 0$.

In the first period, the farmer chooses the quantity of the variable input X to maximize the expected utility of profits, $E_\theta\{U(\pi)\}$. The farmer's choice of X is conditioned on the response of second period labor to fertilizer use. So that now the farmer's maximization problem is given by

$$\text{Max } E_\theta\{U((\bar{\theta}_k + (1-\gamma)\tilde{\theta}_k) f(X,\bar{L}-L(X)) - qX + (\bar{w}_k + (1-d_k)\tilde{\theta}_k)L(X)\} \quad (10)$$

The first-order condition for the first period problem is[4]:

[4]Note that the term $E_\theta\{U' * \partial L/\partial X\{(\bar{w}_k+(1-d_k)\tilde{\theta}_k-(\bar{\theta}_k+(1-\gamma)\tilde{\theta}_k f_l\}$ is zero by the first order condition in (4). Nonetheless, the fact that L is a function of X will affect the comparative statics

$$E_\theta U'[(\bar{\theta}+(1-\gamma)\tilde{\theta})\ f_x(X,\bar{L}-L(X))\ -\ q]\ =\ 0\ . \qquad (11)$$

Denote $Z_x = (\bar{\theta}_k+(1-\gamma)\tilde{\theta}_k)\ f_x(X,\bar{L}-L(X))\ -\ q$. Since the covariance between U' and Z_x is negative, the farmer under-utilizes fertilizer, in the sense that the expected marginal product of fertilizer is greater than its price. Thus expected profits could be raised by increasing fertilizer use. Second order conditions require that the total differential of (11) be negative, e.g.

$$\Delta\ =\ E_\theta U''Z_x^2\ +\ EU'(\bar{\theta}_k+(1-\gamma)\tilde{\theta}_k)(f_{xx}-f_{xl}\partial L/\partial X)\ <\ 0. \qquad (12)$$

Note that the first term is negative since U''<0 everywhere. Substituting for $\partial L/\partial X$ from above, the second term becomes $E_\theta\ U'(\bar{\theta}+(1-\gamma)\tilde{\theta})(f_{xx}-f_{xl}^2/f_{ll})$. By assumption U' > 0 and $\bar{\theta}_k\ +\ (1-\gamma)\tilde{\theta}_k\ >\ 0$ everywhere. By concavity of the production function the term $(f_{xx}-f_{xl}^2/f_{ll})$ is negative, so that the second term above is negative, and the second order conditions are satisfied.

In Section II I showed that as labor markets deepened, as represented by a falling unemployment rate, fertilizer use in the ICRISAT sample rose, especially in Aurepalle and Shirapur. The response of fertilizer demand to d, which measures the depth of the local labor market, captures this effect in the model. Totally differentiating (11) and rearranging yields

$$\partial X/\partial d_k\ =\ E_\theta U''\{(-\tilde{\theta}_k L)[(\bar{\theta}_k+(1-\gamma)\tilde{\theta})_k f_x-q]\}\ -\ E_\theta U'\{[\bar{\theta}_k+(1-\gamma)\tilde{\theta}_k]f_{x1}\partial L/\partial d_k\}/-\Delta \qquad (13)$$

Substituting for $\partial L/\partial d_k$ from above yields

$$\partial X/\partial d_k\ =\ \frac{E_\theta U''\{-\tilde{\theta}_k L\}[\bar{\theta}_k+(1-\gamma)\tilde{\theta}_k]f_x-q\}\ -\ E_\theta U'\tilde{\theta}_k f_{x1}/f_{ll}}{-\Delta} \qquad (14)$$

The denominator is positive by the second order conditions. Under the assumption of constant absolute risk aversion, the first term in the numerator is positive, since $E_\theta U''\tilde{\theta}[\bar{\theta}+(1-\gamma)\tilde{\theta}]f_x-q\}$

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of X, especially the response to risk.

$= E_\theta U''(-\tilde{\theta})Z_x$ which is negative (Feder, p. 508). The second term is negative, since $f_{ll} < 0$ and $cov(U', \tilde{\theta}) < 0$. Therefor, $\partial X/\partial d_k > 0$ holds if the first term is greater (in absolute value) than the second term.

Likewise, the response of fertilizer demand to the expected wage, $\partial X/\partial \bar{w}_k$ can be derived, again utilizing $\partial L/\partial \bar{w}_k$ from above:

$$\partial X/\partial \bar{w}_k = \frac{L * E_\theta U'' Z_x - E_\theta U' f_{x1}/f_{ll}}{-\Delta} \tag{15}$$

The first term is positive, while the second term is negative, so that $\partial X/\partial \bar{w}_k > 0$ holds if the first term dominates.

IV. Empirical estimates of fertilizer demand

The optimization problem described above gives rise to highly nonlinear relationships for fertilizer demand which depends on parameters of the production technology and the utility function. Estimating the structural parameters of these demand relationships is beyond the scope of this paper. Rather, I estimate linear approximations to the underlying fertilizer demand functions arising from equation (10) above. The optimization problem results in a notional demand for fertilizer of the form:

$$X_{it}^* = \alpha + Z_{it}B + u_{it} \tag{16}$$

where *it* refers to household i at time t. Z_{it} is a vector of regressors and B is a coefficient vector to be estimated; u_{it} is a random error term. While X_{it}^* may well be negative, we observe in practice X_{it} which is zero if $X_{it}^* \leq 0$ and equal to X_{it}^* otherwise. This is the classical Tobit regression model.

A further complication arises in the empirical model because we observe the same households over time. If the disturbance term in (16) is written as $u_{it} = \delta_i + \epsilon_{it}$, where ϵ_{it} is a white noise error term, with zero mean, finite variance, and $E\{\epsilon_{it}\,\epsilon_{jt}\} = 0$ for all $i \neq j$ and $E\{\epsilon_{it}\,\epsilon_{is}\} = 0$ for all $s \neq t$ then efficient estimation depends on the nature of δ_i. If δ_i is constant across households, and if it is correlated with household characteristics that are included in the vector of regressors Z_{it}, then failing to correct for the presence of fixed effects results in biased and inconsistent estimates of the parameters in B, and of course, biased tests of parameter significance as well. On the other hand, if δ_i is a random variable which represents an additional source of error, in the regression, then correcting the estimates for the error introduced by δ_i using a random-effects specification will allow for more efficient estimates of the parameters of B.

Whether random effects or fixed effects is appropriate is, of course, an empirical question. I estimate fertilizer demand and off-farm labor supply using both methods below and test for the appropriateness using the method suggested by Hausman. While I find evidence that there are fixed effects in the model, I report both fixed and random effects for comparison. Moreover, the use of random effects allows for identification of factors that may be fixed for a given household, such as the riskiness of the production environment, e.g. the second moment of the distribution of the random shock.

The key relationship in the model above is that between the depth of the off-farm labor market, d, and the household's demand for fertilizer, which must be made in advance of the resolution of production risk related to weather. Measuring the depth of the local labor market is a complicated question. A Keynesian approach would be to utilize the degree of "involuntary unemployment" that exists in the local labor market as a measure of how well the labor market works. To the extent that some workers are unable to obtain employment at the prevailing wage, then the labor market is less useful as a hedge against negative production shocks.

A more direct measure of depth in the context of the semi-arid tropics is the share of total employment in the local labor market that is not dependent on agriculture. If labor markets offer opportunities for farm laborers to participate in non-agricultural activities then wage levels and access to employment will be less dependent on shocks to agricultural production. In fact, the government Maharashtra instituted a work guarantee scheme to provide non-agricultural employment for farm laborers (Walker and Ryan, p.62).

In this paper, I take an empirical approach to choosing an appropriate measure of the depth of the village labor market. I construct measures of both involuntary unemployment and the share of nonagricultural employment at the village level for 1979 through 1983 and estimate fertilizer demand conditional on both measures. Since there are well-known and rigid gender differences in agricultural production tasks, I construct both measures by gender.

I used detailed information contained in Schedule K of the ICRISAT data on the labor market activities of sample households to construct both gender-specific unemployment rates and shares of non-agricultural employment. From 1979 to 1984 information was collected on the number of days individual members of the households worked on-farm and off-farm in both agricultural production, and a number of types of nonagricultural activities. In addition, information on the number of days in the sample period during which workers looked for work, but were unable to obtain it, was also collected. I calculated total labor supply by adding up days worked in all activities, *except on-farm production work.* I calculated unemployment rates for both planting period and harvest period activities by village, where the numerator is days unemployed and the denominator is days in the labor market (excluding on-farm work days), both summed across all households in the village. Since this detailed information is only available from 1979 onward, the sample period used in estimation is somewhat restrictive. The unemployment rate is a measure of (1 - d), or more generally, is negatively related to the depth of the labor market.

As an alternative measure of the depth of the village labor market, I calculated the share of total labor market activities that took place in the non-agricultural sector, again by gender and during the planting period only. The greater the share of labor market activities that are in the nonagricultural sector, the deeper the village labor market, and the more immune are village wages to agricultural production shocks. Again, I excluded on-farm work from the calculation, and the variables are created at the village level.

An important question that must be addressed in the empirical analysis is the amount of information about the village labor market available to the household at the time it must choose its fertilizer level. Obviously, since the monsoon has not run its course, households have less than perfect information about village wages in the post-harvest period and, also, about their access to the labor market in the case of a negative production shock. Therefor, in estimating fertilizer demand I condition only on information available to the household during the first period of the model above, e.g. before rainfall uncertainty is completely resolved.

Table I contains a summary of variables used in estimation. I distinguished between activities that occurred before the end of the monsoon, period one in the model, using Rosenzweig and Binswanger's (1993) definition of the monsoon onset and end dates. Period-specific wages were defined using information on time and type of task.[5] The village average wage in agriculture is divided by the village consumer price index (Walker and Ryan, 1990, p. 28) to create the real village-level wage by gender for the first period. The real price of chemical fertilizer in the village is calculated as the price of urea adjusted for inflation.[6] The share of cropped area that is irrigated is an important measure of the household's ability to deal with risk (e.g. it corresponds to γ in the model above).

Estimates of the fertilizer demand equation conditional on prices, wages, and measures of village-level risk are reported in Table 2. Random effects Tobit model estimates are reported in column (1), using the share of nonagricultural employment as a measure of labor market depth and in column (3), using the unemployment rate to measure labor market depth.[7] The most important finding here is that the level of fertilizer demand is positively related to the depth of the village labor market, whether measured using the unemployment rate or the share of non-agricultural employment. For estimates conditional on the share of nonagricultural employment, both male and female shares of nonagricultural employment in period 1 are statistically significant at the five percent level and positive, as predicted in the model above. The variables measuring

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[5]The structure of the ICRISAT questionnaire changed in 1979; from 1975 to 1978 respondents were asked how many hours they worked *the previous day* in various activities. After 1978 households were asked how many hours they had worked *since the last interview*.

[6]In fact, by the end of the sample period farmers use a wide variety of complex fertilizers on their crops. However, urea is a common fertilizer used in all the ICRISAT villages in every year. The price of chemical fertilizers should move together, so using the price of urea should not bias results.

[7]Estimation of the random-effects Tobit model is achieved using maximum likelihood techniques in *Stata*, Release 7. For a fuller discussion of the methodology, including the likelihood function, see the Stata Reference Manual, Release 7, Volume 4, pp. 446 - 450.

the standard deviation in four measures of the timing and extent of the monsoon are jointly statistically significant at the 1 percent level, as are their interactions with female share of non-agricultural employment in the village labor market. The real price of fertilizer and the real wage for female laborers is negative and statistically significant at the 1 percent level, as one would expect if fertilizer use and production labor are complements. Neither the male wage nor the monsoon onset date is not statistically significant at even the 10 percent level.

Random effects Tobit estimates conditional on the first-period unemployment rate for male and female laborers, column 3 of Table 2, are quite similar, although somewhat weaker. The level of male unemployment is statistically significant at the1 percent level and negative as expected, but the level of female unemployment is not significant at even the 10 percent level. However, the interaction terms between female unemployment in the first period and the measures of village-level weather risk are significant at the 10 percent level. Variables measuring the dispersion of rainfall uncertainty are jointly significant at the 1 percent level. Wealthier farmers use more fertilizer on average, consistent with lower levels of risk aversion or greater access to ex-post consumption smoothing, and the share of the household's cropped area that is irrigated raises fertilizer use. The real fertilizer price is significant at the 1 percent level, but male and female wages are not jointly significant at even the 10 percent level.

For estimates conditional on either unemployment or nonagricultural employment, I can reject the null hypothesis of no fixed effects at the five percent level. Therefor, I also estimated parameters of fertilizer demand using a fixed-effects Tobit estimator.[8] Including a household

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[8]Failure to control for fixed effects will bias estimates if there are included variables which are correlated with the omitted fixed-effect terms.

dummy variable and then running the standard Tobit estimation routine yields results which are not consistent as the number of individuals increases and the number of time periods is constant. Consider the case of fertilizer demand X^*_{it} from equation (16). Honore (1992) shows that if u_{it} and u_{it+1} are independent and identically distributed conditional on the regressors Z_{it}, Z_{it+1} then the distribution of the latent dependent variables X^*_{it} and X^*_{it+1} is distributed symmetrically around the 45-degree line that passes through $(\Delta Z\beta, 0)$, where $\Delta Z = X_{it+1} - X_{it}$. Because the symmetry is not affected by censoring, the observed fertilizer demands are also distributed symmetrically. Symmetry suggests orthogonality conditions which must hold at the true parameter values, and these orthogonality conditions form the basis for the estimator. The Honore estimator takes the squared value of all the trimmed deviations $(X_{it+j} - X_{it})$ across all households and all possible time pairs contained in the data. The objective funtion is minimized using numerical methods implemented in Gauss.[9] Honore shows that the trimmed estimator is consistent and asymptotically normal when the underlying model is accurately described by fixed effects. Since the estimator does not estimate the fixed effects directly, it is consistent as the number of individuals goes to infinity, but the number of time periods is fixed. This approach is ideally suited for the case of short panels, such as the ICRISAT data.

Results for fertilizer demand using Honore's fixed-effects Tobit estimator are reported in columns 2 and 4 of Table 2. The dependent variable is fertilizer use per hectare of total cropped area. Because differencing across time periods in the fixed effects estimator eliminates variables that are constant across time for individuals, it is not possible to estimate the direct impact of the

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[9]I am grateful to Professor Bo Honore of Princeton University for making available the Gauss code to implement the estimator. The software may be downloaded from the web at http://web.princeton.edu/sites/econometrics/programs/pantob/.

standard deviations in the rainfall variables. The coefficient estimates for the remaining variables reflect the within household variation only. For estimates conditional on the share of nonagricultural employment in the off-farm labor market, column 2, the coefficient on the share of irrigated land is positive and significant at the 1 percent level. Neither fertilizer price nor the wages are statistically significant at even the 10 percent level. The shares of non agricultural employment are both positive as expected, and the variables measuring the interaction of the shares with the the standard deviation of the rainfall shock are jointly statistically significant at the 1 percent level.

For the model of fertilizer demand conditional on unemployment rates, column 4 of Table 2, the share of irrigated land is significant and positive, while the wages and prices are not statistically significant. The first-period male unemployment rate is statistically significant and negative at the 10 percent level, and the unemployment rates are jointly significant at the 10 percent level as well. The variables measuring the interaction of unemployment rates with the variance of rainfall measures are jointly significant at the 10 percent level as well.

That the fixed-effects results are less forceful than the random effects results is not surprising. By sweeping out all the factors that are constant across time within a household, including characteristics of the distribution of village-level shocks that are not measured directly and the household's own appetite for risk-taking, the fixed effects model leaves the less variation for the data to explain (hence, the much larger standard errors in the fixed-effects model). The fact that the variables measuring the depth of the village labor market continue to be important in explaining the residual variation in fertilizer demand suggests that there is an important relationship between the household's access to off-farm employment as a hedge and its willingness to use fertilizer.

V. Conclusion

I develop a two-period stochastic dynamic programming model to show that fertilizers will use more fertilizer the deeper is the off-farm labor market. I use a well-known data set on a sample of farmers in the semi-arid tropics of India to test the model. I find that the farmers use more fertilizer as the depth of the off-farm labor market increases, where depth is measured using both the unemployment rate and the share of employment in nonagricultural activities. Moreover, the interaction between the depth of the labor market and the degree of riskiness is important in explaining fertilizer use. This suggests that what is being measured is, in fact, the importance of the labor market in second-period consumption smoothing.

These results have important implications for development policy. While it is tempting to view off-farm work and farm production as substitutes, so that policies designed to raise the one must come at the expense of the other, the results here suggest that there are important complementarities between farm production and off-farm work. These complementarities suggest that policies that deepen the off-farm labor market may promote more intensive on-farm production as well, particularly where such policies focus on the role off-farm labor may play in consumption smoothing ex-post. The results highlight the need for further study of the dynamics of agricultural production in developing countries.

Table 1

Means for Variables Used in ICRISAT Models[10]

Fertilizer use per acre	9.82
Real fertilizer price	2.44
First-period real wage, male (Rupees/hour)	0.86
First period real wage, female (Rupees/hour)	0.54
First-period unemployment rate, males	0.15
First-period unemployment rate, females	0.15
Share of non-agricultural employment, males	0.59
Share of non-agricultural employment, females	0.36
Share of crop area irrigated	0.11
Household's real assets (1000 Rupees)	21.7
Standard deviation, monsoon onset (days)	15.4
Standard deviation, total rainfall	205
Standard deviation, rain per day	1.72
Standard deviation, frequency of rainfall days	0.10

[10]Based on 560 observations used in estimates of fertilizer demand, drawn from five of the ICRISAT study villages. Values for the whole ICRISAT sample may differ.

Table 2

Tobit Estimates for Fertilizer Demand
Dependent Variable: Fertilizer Demand Per Hectare[11]

	(1) (Random Effects)	(2) (Fixed Effects)	(3) (Random Effects)	(4) (Fixed Effects)
Real fertilizer price	-16.43**	-5.85	-12.63**	-1.53
	(-2.39)	(-0.56)	(-2.40)	(-0.21)
Monsoon onset date (deviation from village mean)	-2.47	-0.23	-9.04	-0.17
	(-0.17)	(-0.92)	(-0.68)	(-0.83)
Share of irrigated land	52.23***	67.17***	49.42***	60.59***
	(9.13)	(3.46)	(8.66)	(4.42)
Real wage for male labor, Planting period	5.88	-13.97	-6.44	-38.69
	(0.30)	(-0.58)	(-0.28)	(-1.09)
Real wage for female labor, planting period	-79.87***	-28.07	-49.4	7.05
	(-2.32)	(-0.36)	(-1.40)	(0.14)
Real value of household assets	20.5***	-2.42	21.89***	0.56
	(3.76)	(-0.37)	(3.99)	(0.06)
Standard deviation - monsoon onset	-3.27		0.40	
	(-0.86)		(0.51)	
Standard deviation - total rainfall	17.38*		-0.35	
	(1.84)		(-0.55)	
Standard deviation - rain per day	-1351*		30.8	
	(-1.62)		(0.54)	
Standard deviation - frequency of days with rain (X1000)	23.8*		60.53	
	(1.89)		(0.74)	
Share of non-ag labor in female labor, planting period	4347.9**	3069.		
	(2.17)	(1.29)		
Share of non-ag labor in male labor, planting period	44.02***	33.69		
	(2.75)	(1.41)		
SD monsoon onset X share of non-ag, female planting period	-4.46	-14.89		
	(-0.85)	(-1.45)		

[11] t-statistics are shown in parentheses.

Table 2, continued

	(1)	(2)	(3)	(4)
SD total rainfall X share of- non-ag female planting period	-21.18* (-1.93)	-11.27 (-0.76)		
SD rainfall per day X share of non-ag, female, planting period	1.55* (1.60)	595.7 (0.45)		
SD frequency of rain days X share of non-ag, female planting period	-25.65* (-1.75)	-1.48 (-0.80)		
Unemployment rate, males planting period			-128.06** (-2.29)	-105.6* (-1.73)
Unemployment rate, female, planting period			-2589.9 (-1.28)	-795.3 (-0.37)
SD monsoon onset X planting period, female UR			-10.38 (-1.44)	-7.80 (-0.83)
SD total rainfall X planting period, female UR			14.62 (1.28)	5.30 (0.42)
SD Rain Per Day X Planting Period, Female UR			1093.8 (-1.09)	-319.0 (-0.29)
SD Frequency of Rain Days X Planting Period, Female UR			16.91 (1.14)	4272 (0.27)
X^2-test for significance of wages[12]	5.54* (0.06)	2.11 (35.4)	2.92 (0.23)	1.7 (42.7)
X^2 - test for significance of rainfall dispersion	30.01** (0.00)		49.24*** (0.00)	
X^2 -test significance of interaction SD in rainfall and labor market depth	24.2*** (0.00)	14.5*** (0.01)	8.19* (0.08)	8.1* (0.09)
X^2 - test for significance of labor market depth	8.44*** (0.01)	2.1 (35.7)	5.29* (0.07)	4.8* (0.09)
X^2- test for null hypothesis of no fixed effects	27.09** (0.01)		24.02** (0.02)	

[12]For X^2 tests, p-values are shown in parentheses.

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Figure 1.1
Fertilizer Use in Aurepalle

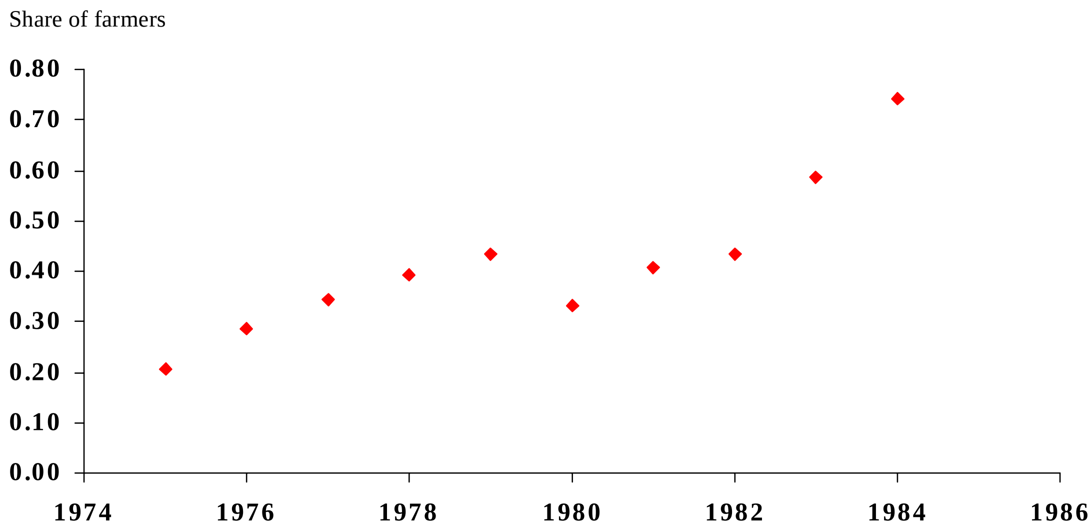

Figure 1.2
Fertilizer Use in Shirapur

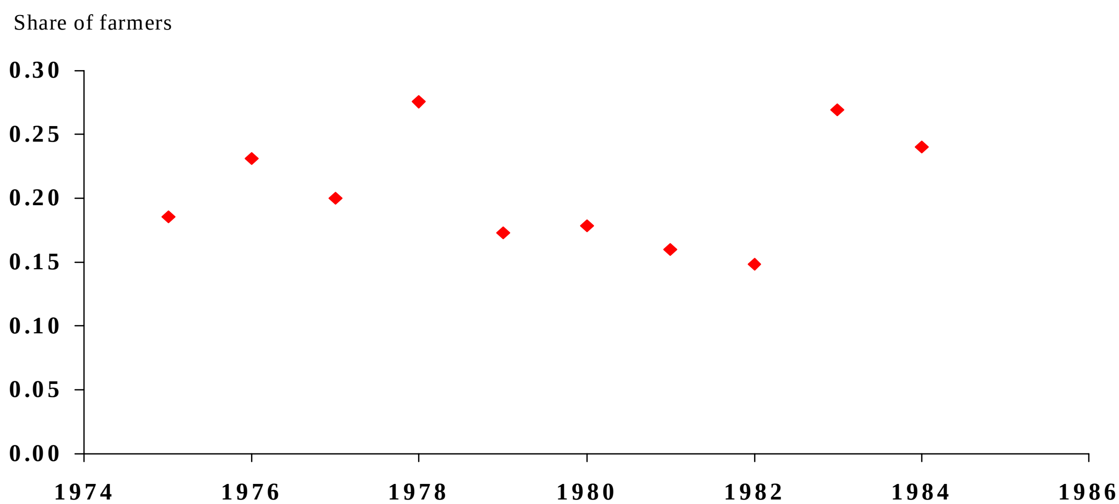

Figure 1.3
Fertilizer Use in Kanzara

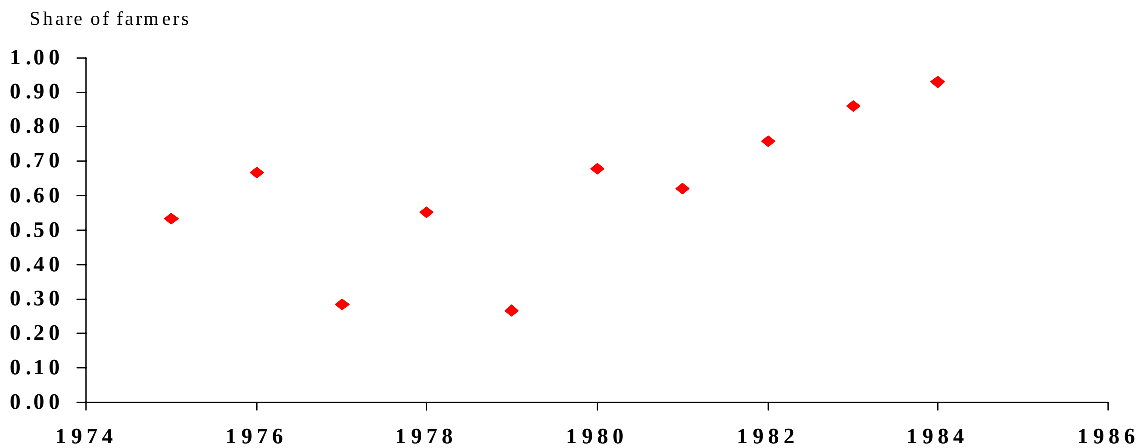

Figure 2
Monsoon Fertilizer Use as a Share of Total

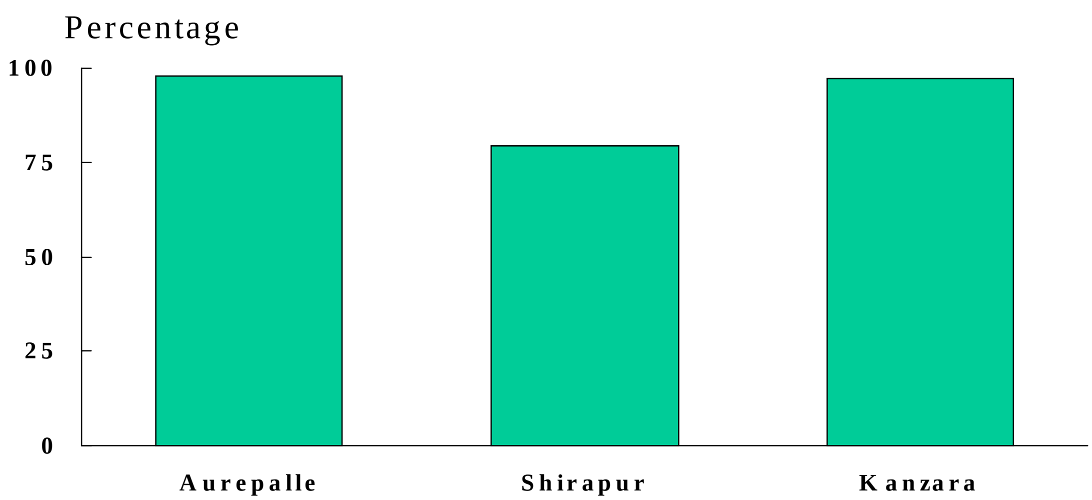

Figure 3
Share of total off-farm labor in the first period

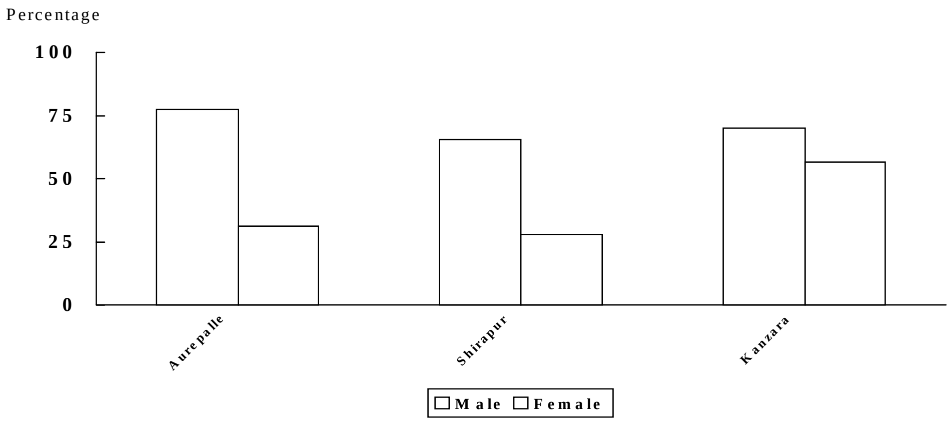

Figure 4
Unemployment and fertilizer use