AN ABSTRACT OF THE THESIS OF

HEUNG-DONG LEE for the DOCTOR OF PHILOSOPHY in AGRICULTURAL AND RESOURCE ECONOMICS presented on DECEMBER 21, 1989 .

Title: INPUT DEMAND AND OUTPUT SUPPLY RESPONSES WHEN THE PRODUCTION FUNCTION IS HETEROSKEDASTIC

Abstract approved: Redacted for privacy

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Risky situations are ubiquitous in the real world. This study focuses particularly on yield uncertainty in Iowa corn production and Oregon wheat production. The Von Neumann-Morgenstern expected utility theorem is employed to explain farmers' responses to this risky production. Multiplicative (Cobb-Douglas) functional forms are used to model corn production in three Iowa counties and linear-quadratic forms are employed to model wheat production in one Oregon county.

Two methods are introduced to estimate the parameters of heteroskedastic production functions. The first is the Just-Pope method, which uses ordinary least-squares estimators. The second is a systems method, which uses a nonlinear three stage least squares estimator with cross-equation restrictions. In the systems method, input uses are simultaneously determined through a system of input demand equations and a production function. The Hausman specification test is employed to test whether there is simultaneity in the input demands in Iowa corn production. The hypothesis of no simultaneity is not rejected for Fayette, Linn, and Muscatine Counties. The average farmer is shown to be risk averse in all three counties.

Systems parameter estimates are used to trace output supply and

input demand functions for both risk neutral and risk averse farmers in Linn and Muscatine counties. Risk averse producers demand substantially less fertilizer, and supply moderately less corn per acre, than do risk neutral producers. The reason is that increases in the application rate of each fertilizer increase yield variance as well as yield mean and risk averters include such risks as part of their costs.

INPUT DEMAND AND OUTPUT SUPPLY RESPONSES WHEN THE PRODUCTION FUNCTION IS HETEROSKEDASTIC

by

Heung-Dong Lee

A THESIS

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Doctor of Philosophy

Completed December 21, 1989

Commencement June 1990

APPROVED:

Redacted for privacy

Professor of Agricultural and Resource Economics
in charge of major

Redacted for privacy

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Date thesis is presented December 21, 1989

Typed by Jungmi Lee for Heung-Dong Lee

ACKNOWLEDGEMENT

The author wishes to gratefully acknowledge the guidance and assistance of Dr. Steven T. Buccola.

Thanks go also to Dr. H. A. Love, Dr. M. V. Martin, Dr. J. C. Cornelius, and Dr. P. J. Ballerstedt, who served on my graduate committee.

Special acknowledgement is made to Dr. L. A. Ihnen for his encouragement during the period of graduate study.

Finally, I wish to acknowledge the contribution of my parents, Seung-Hyo Lee and Yoon-Duk Sul, my wife Jungmi, and my children, Jennifer and Daniel. Only with their patience, understanding, encouragement and sacrifice was this dissertation possible.

TABLE OF CONTENTS

LIST OF TABLES

INPUT DEMAND AND OUTPUT SUPPLY WHEN THE PRODUCTION FUNCTION IS HETEROSKEDASTIC

CHAPTER I

INTRODUCTION

Problem

One of the assumptions of the neoclassical theory is certainty; that is, there is no uncertainty in the input and output prices or in the production relationship. In the real world, there is some uncertainty in prices and/or in the production function. One example is that output price is unknown to the farmer at the time he first applies inputs. He can, in some cases, use futures prices or forecasts based on historical time series. Accuracy of futures prices in predicting cash prices depends on information available to futures traders. When time series data on future prices are used to forecast cash prices, forecasts have a mean and variance. Finally, each farmer may supplement time series data with his own subjective probabilities about future cash prices. Sandmo (1971) shows the supply response under uncertainty about cash output prices. He shows that supply of output under price uncertainty is less than the supply of output under price certainty because risk is an additional cost if the producer is risk averse.

Another example of uncertainty is that the farmer does not know the exact quantity of output at the time of his decisions about inputs because he is uncertain about his production function and about growing season weather conditions such as rainfall and temperature. Just and Pope (1979) discuss proper use of functional forms when there is a stochastic relation between output and input use. They show that the variance of output depends on the structure of heteroskedasticity of the production function's error term. This study focuses on uncertainty in output instead of in prices.

Just and Pope's (1978) parameter estimation of a risky production function uses the ordinary least squares (OLS) method. The OLS estimators assume inputs in the right-hand side of the equation are exogenous variables. However, optimal input levels are endogenous since inputs respond to changes in output prices and input prices. In order to use this endogeneity, systems estimation is required which includes both output supply and input demands.

Objectives

The purpose of this study is to: (1) examine the behavior of a producer's output supply under risk, and (2) compare Just and Pope's method of estimating the coefficients of a risky production function with the use of a systems estimator of a firm's production function, output supply, and input demands.

Specific objectives of this study are to: (1) derive risky supply and input demand functions for wheat in selected Oregon counties and for corn in selected Iowa counties, and (2) estimate output elasticities and risk aversion coefficients for these countries using alternately the Just-Pope and systems estimators.

Thesis Organization

In the following chapter, the theory of input demand and output supply under risky yields is introduced through the use of the expected utility theorem. In Chapter III data requirements are discussed and production, supply, and demand estimations are presented using the two methods. Results and conclusions comprise Chapters IV and V, respectively.

CHAPTER II

DECISION MODEL

Introduction

An individual does not know with certainty the result of his actions when the actions' outcome depends not only on his choice but on the future unknown state of the world. When the future state of the world is assigned instead a probability, it is said to be a risky situation. Since individuals have different attitudes to the risky situation, the von Neumann-Morgenstern utility theorem is useful in explaining individuals' behavior in this case.

Von Neumann-Morgenstern (N-M) Expected Utility Theory

An expected payoff approach does not explain well an individuals' behavior in a risky game. Some individuals won't play a game even if the expected payoff is greater than its expected cost.

A more productive approach is to think in terms of utilities rather than payoffs. The expected utility theorem provides a criterion for an individual's decision among a set of alternative risky options. This theory uses an axiomatic approach under which the individual is assumed to behave rationally.

An N-M utility function evaluates an option's possible outcomes (W_1, ... W_n) with probabilities ($P_1, \ldots P_n$) on the basis of its expected utility $EU = \Sigma U(W_i)P_i$ rather than on the basis of its expected payoff $EW = \Sigma W_i P_i$.

Since the expected utility model relates to individual behavior, each individual has his own utility function. The utility function has a unique shape according to the preference of individual. The (suitably normalized) shape of utility function encodes the risk attitudes of the individual. He is a risk averter with a concave utility function because the utility of the expected payoff is then greater than his expected utility of payoff, [U(EW) > EU(W)], which implies he would prefer a sure payoff to the game in which expected payoff equals the sure payoff. He is a risk lover with a convex utility function because the utility of expected payoff is less than the expected utility of payoff, [U(EW) < EU(W)], which implies he would choose a sure payoff instead choosing the game in which expected payoff equals the sure payoff. He is risk neutral with a linear utility function because his utility of expected payoff is the same as the expected utility of payoff [U(EW) = EU(W)], implying he is indifferent between a sure payoff and the game in which expected payoff equals the sure payoff. In this latter case, there is no difference between the expected payoff approach and the expected utility approach. Friedman and Savage (1948) showed how an individual's behavior may differ according to his wealth position. His utility function may be concave at low wealth levels and convex at high wealth levels. This utility shape explains the behavior of an individual who buys insurance to avoid risk and purchases a lottery ticket involving risk.

The expected utility function is unique up to a positive linear transformation. Such a transformation changes the origin and scale of the utility and expected utility, but does not affect the essential shape of the function or the decision maker's risk attitude. Therefore, a positive linear transformation can be used to normalize any N-M utility function.

The degree of curvature of the individual utility function tells us about the magnitude of an individual's attitude toward risk. The point of payoff which maps into the expected utility of a particular risky prospect is that prospect's certainty equivalent. The difference between the prospect's certainty equivalent and its expected payoff is the prospect's risk premium. Risk premium depends upon both the variability of the risky prospect and the risk aversion of the decision maker. The risk premium (RP) contains information about risk aversion as well as risk. Pratt (1964) shows that it is approximately $\sigma^2 r(W)/2$, where σ^2 is risk and $r(W)$ is risk aversion.

Optimal Input Use

If an individual follows the axioms of expected utility, his preferred choice among several options is the one that has highest expected utility. Expected utility is a function of the factor which brings utility, which in the present model is profit. The profit function depends in turn on the form of production function assumed. Consider first the Cobb-Douglas production functional form, $y = A\pi x_i^{ai}\exp(e)$, the variance of which is $V(y) = A^2(\pi x_i^{2ai})V(\exp(e))$. To determine the marginal effect of the ith input on output variance, take the first derivative of $V(y)$ with respect to x_i : $dV(y)/dx_i = 2a_iA^2(\pi x_i^{2ai})V(\exp(e))/x_i$. a_i is positive when expected marginal productivity of input x_i is positive. Therefore, the marginal effect on output variance is positive if and only if $a_i > 0$, which implies increasing input levels always increase the variability of output if they increase output mean. Unfortunately, some inputs such as pesticides or irrigation water can reduce variability in output even as they increase the output expectation. It is reasonable, in other words, that some expected-yield-improving inputs may increase yield variability while others reduce yield variability.

The Just-Pope production functional form handles such flexibility well. This function has both a mean and an additive variance portion. The output elasticity mean is obtained from the mean portion and the variance of the output elasticity is obtained from the variance portion. Therefore, an input's marginal effects on mean and variance of output are calculated separately.

The Just-Pope production functional form is:

$$y = f(x) + h(x)e \qquad (1)$$

where y is output, x is a vector of nonstochastic inputs, and e is a normally distributed random error with zero mean and variance of one. The function h(x)e indicates this production function is heteroskedastic because the magnitude of h(x)e depends on the level of inputs.

The farmer's profit function is

$$W = Py - rx \qquad (2)$$

where P and r are assumed nonrandom output and input prices. Substituting (1) into (2) gives

$$W = P[f(x) + h(x)e] - rx \tag{3}$$

Suppose the objective of producers is to maximize their expected utility of profit, that is,

$$\text{Max } EU(W) \tag{4}$$

Then each producer has to decide how much input x he will use to maximize his expected utility of profit.

Substituting (3) into (4) gives

$$\text{Max } EU\{P[f(x) + h(x)e] - rx\} \tag{5}$$

To determine the optimal input levels, obtain the first order conditions of (5) with respect to the inputs. The first order conditions are

$$E\{U'(W)[Pf_i(x) + Ph_i(x)e - r_i]\} = 0 \quad \text{all } i \tag{6}$$

where f_i and h_i are first derivatives with respect to the ith input. Manipulating equation (6) gives $Pf_i(x)E[U'(W)] + Ph_i(x)E[U'(W)e] = r_iE[U'(W)]$, all i, or, dividing by $E[U'(W)]$,

$$Pf_i(x) + Ph_i(x)\{E[U'(W)e]/E[U'(W)]\} = r_i \quad \text{all } i \tag{7}$$

In general, therefore, each optimal input x_i is specified as

$$x_i^* = x_i\{P, r, E[U'(W)e]/E[U'(W)]\}. \tag{8}$$

For each input i, $E[U'(W)e]$ in equation (7) equals $E[U'(W)]E[e] + \text{cov}[U'(W), e]$. However, $E[U'(W)]E[e]$ is zero because $E[e] = 0$. Hence, $E[U'(W)e] = \text{cov}[U'(W), e]$. So equation (7) can be rewritten as

$$Pf_i(x) + Ph_i(x)\{cov[U'(W),\ e]/E[U'(W)]\} = r_i \quad \text{all } i \qquad (9)$$

Term $k(W) = cov[U'(W),\ e]/E[U'(W)]$ tells us about the individual's degree of risk aversion as well as about the magnitude of the risk. For the risk neutral producer, $cov[U'(W),\ e]$ is zero since $U'(W)$ is constant as e and thus W varies. First order condition of equation (9) becomes

$$Pf_i(x) = r_i \quad \text{all } i \qquad (10)$$

For the risk neutral individual, that is, the expected value of marginal product equals input price as in neoclassical theory.

Generally, the second term in equation (9), $Ph_i(x)k(W)$, represents a marginal risk premium, the sign of which affects optimal input levels. This risk premium is composed of two components. The first component, $P[h_i(x)]$, tells us about the effect on the variability of output value of a change in the ith input level. If production variance increases as the ith input use rises, this term will be positive ($Ph_i(x) > 0$). If production variance decreases as the ith input use rises, the term will be negative ($Ph_i(x) < 0$).

Consider now the second part, $k(W) = cov[U'(W),\ e]/E[U'(W)]$, of the second term in (7). The greater algebraically is the random error e, the greater is profit W. And if the decision maker is risk averse with concave utility, the greater profit will result in lower marginal utility $U'(W)$. Thus, $cov[u'(w),\ e]$ is negative under the assumption of risk aversion, $u''(w) < 0$. On the other hand if the producer is a risk lover, the term will be positive.

It follows from the above that if the producer is risk averse and the variance of production increases as input use rises, the second term in equation (7) will be negative. This implies that the producer's optimal input use will be at the point where the expected value of marginal product is greater than input price, $Pf_i(x) > r_i$. That is, he uses more of this input than does the risk neutral individual. If he is a risk averter and production variance decreases with input use, the second term in equation (7) will be positive, implying the producer's optimal input use will be at the point where the expected value of marginal product is less than input price, $pf_i(x) < r_i$. That is, assuming $f_{ii}(x) < 0$, he uses more of this input than does the risk neutral individual. Finally, if the production function is homoskedastic ($h_i(x) = 0$), the optimal level of input use equals the neoclassical optimal level even if the producer is risk averse or a risk lover because in that case $k(W)0 = 0$.

In general, therefore, optimal choice between inputs depends on relative heteroskedasticity as well as on relative input prices. Note that the first order condition for the jth input is

$$Pf_j(x) + Ph_j(x)k = r_j$$

while for the ith input it is

$$Pf_i(x) + Ph_i(x)k = r_i.$$

Taking the ratio of these equations gives

$$f_j(x)/f_i(x) = [r_j - ph_j(x)k]/[r_i - ph_i(x)k]$$

For the neoclassical solution (where there is no risk and hence $h_i(x) = h_j(x) = 0$), marginal rate of technical substitution (MRTS = $f_j(x)/f_i(x)$) equals the relative input price (r_j/r_i). However, when the production function is heteroskedastic, optimal input choices do not lie on this neoclassical expansion path. Instead, the isocost line is nonlinear with slope:

$$\{r_j - Ph_j(x)E[U'(W)e]/E[U'(W)]\}/\{r_i - Ph_i(x)E[U'(W)e]/E[U'(W)]\}.$$

Approaches to Estimation

The above suggests it is useful to know the structure of heteroskedasticity, h(x), in the production function. One approach to estimating h(x) is to follow the procedures laid down in Just and Pope (Just and Pope, 1979). First, use nonlinear least square (NLS) to obtain the parameters α of the mean portion, f(x), of (1), where h(x)e is random error u:

$$y = f(x|\alpha) + u \tag{11}$$

Second, take the absolute value of the log of the residual u and regress it using ordinary least squares (OLS) on log h(x)e = log h(x) + log e to estimate the parameters β of h(x):

$$\log |u| = \log h(x|\beta) + \log |e| \tag{12}$$

Third, transform (11) by dividing by heteroskedastic term $h(x|\beta)$ so that (11) is in the form of a homoskedastic equation:

$$y/h(x) = f(x|\alpha)/h(x|\beta) + e \tag{13}$$

Then, fit (13) with NLS to obtain revised estimates of α.

Least squares estimation of α in equation (11) is consistent even if the disturbance is not homoskedastic. But the least squares estimates are not asymptotically efficient for any sample size. Dividing equation (11) by heteroskedastic term $h(x|\beta)$ does give consistent and asymptotically efficient estimates of α (Kmenta, 1971). Estimates of β obtained in step (12) are consistent but asymptotically inefficient. They also may be biased in small samples. Buccola and McCarl (1986) showed inefficiency and bias in β and inefficiency in estimates of α may be improved by continuing to iterate in the manner of (12) and (13). It was chosen here to iterate only one further time on β, that is, by logging e in (13) and regressing it on log h(x) to obtain revised estimates of β.

An alternative approach is to estimate f(x) and h(x) by looking at producers' optimal responses to these functions in the form of their output sales and input purchases. That is, it may be more useful to estimate producers' technologies by referring to their behavior in the form of their input demand and output supply functions. Substituting the input demand functions (8) into the production function (1) gives the output supply function:

$$
\begin{aligned}
y^* &= f(x^*) + h(x^*)e \\
&= f\{x^*(P,\ r,\ E[U'(W)e/E[U'(W)])\} \\
&\quad + h\{x^*(P,\ r,\ E[U'(W)e]/E[U'(W)e])\}e \qquad (14) \\
&= y_1(P,\ r,\ E[U'(W)e]/E[U'(W)]) \\
&\quad + y_2(P,\ r,\ E[U'(W)e]/E[U'(W)])e
\end{aligned}
$$

where x^* is the optimal input vector and y^* is the optimal output given e. Equation (14) shows that we have to know the optimal input demand x^* to estimate the supply function.

The random error of the second term in production function (1) potentially makes the output supply function stochastic in the input prices; that is, estimation of supply function (14) may require a GLS approach due to the potentially heteroskedastic error. To see this, take the expectation of equation (14), giving expected supply

$$E(y^*) = y_1\{P, r, E[U'(W)e]/E[U'(W)]\}. \tag{15}$$

Taking the variance of equation (11) gives supply risk

$$Var(y^*) = y_2^2\{P, r, E[U'(W)e]/E[U'(W)]\} \tag{16}$$

since $Var(e)=1$.

One can test whether output supply y^* is heteroskedastic by testing whether y_2 in (14) and in (16) has the required form. From equation (14), the supply function is homoskedastic if and only if $dh/dr_i = (dh/dx_i^*)(dx_i^*/dr_i) = 0$ for all i. This last equation requires that either or both terms dh/dx_i^*, dx_i^*/dr_i be zero for all i. Now $dh/dx_i^* = 0$, all i, means the production function is not heteroskedastic in input levels. In addition, $dx_i^*/dr_i = 0$, all i, says input demands are vertical because demand quantities do not change as prices change. Because input demands typically are not vertical, heteroskedasticity in the production function is usually a necessary and sufficient condition for a supply function to be heteroskedastic in input prices, regardless of the presence of risk aversion. On the other hand,

$E[u'(W)e]/E[u'(W)]$, and thus risk preferences and profit risk, affect through y_2 the magnitude of supply's heteroskedasticity in input prices.

Estimating equation (14) is important because if y_2 is not zero then input or output price changes affect the variance as well as mean of output supply. This implies that the nature of production risk affects optimal input levels and optimal output supply distributions in a manner determined by producers' risk aversion.

Using a systems estimator has potential econometric advantages over the Just-Pope model. If the coefficients of the input demands (7) are the same as those in production function $y = f(x|\alpha) + h(x|\beta)e$, one obtains lower variances of coefficient estimates by including (13) because more restrictions and information in the systems estimator are used. Thus, assuming producers are expected utility maximizers, efficiency over the Just-Pope method is gained if the entire system of equations is estimated with input demand (7) and production function (13).

CHAPTER III

ECONOMETRIC ESTIMATION

Data Requirements and Sources

This study analyzes corn production in Fayette, Linn, and Muscatine Counties in Iowa and wheat production in Crook County in Oregon. Parameters of production function (1) are estimated using (i) Just and Pope's method and (ii) a systems estimator of equations (7) and (13). Clearly, the systems estimator provides an estimate of risk preferences as well as of production function parameters.

To develop either of these approaches, information is needed about output and input levels. For the Iowa study, corn yields per acre at the individual farm level are used as output variables. Fertilizer is the principal variable input in corn production. Input variables modelled in the Iowa study include nitrogen, phosphorus, potassium, ground slope, soil clay content, and dummy variables indicating whether a nitrogen-fixing crop had been planted one or two years ago. Dummy variables were never significant for the three Iowa counties and were dropped in further estimations.

For the Oregon study, the data for wheat production include total wheat yields and acreage planted in each county. Total wheat yields were divided by total acreage planted to obtain yields per acre. Fertilizer is a major input variable in wheat production, also. Input variables modelled in the Oregon study were nitrogen, phosphorus, and acreage planted.

The data for the Iowa counties consists of farm-level information per acre during 1964-1969. The numbers of observations used for Fayette, Linn, and Muscatine Counties, were 106, 103, and 55, respectively. Thus, the Iowa data set is a time series-cross sectional one. The Oregon data set, by contrast, is a purely time series one employing aggregated county-level information from 1964 to 1987. For the Oregon county, the number of observations used for estimation was 24.

In order to estimate input demand equations for the systems approach, information is also needed on output and input prices. To represent corn price expectations, averages of high and low futures prices quoted for contracts in March maturing the coming September at the Chicago Board of Trade were used. Ground slope and soil clay content were assumed predetermined variables and input decisions on the Iowa farms were restricted to nitrogen, phosphorus, and potassium application rates. Appropriate fertilizer price data are given on a state-by-state basis in annual issues of USDA's Agricultural Prices and in Agricultural Resources: Situation and Outlook Report.

For the Oregon study, total wheat yields, total acreage planted, and average wheat price in each county were obtained from the Oregon State University Agricultural Experimental Station. Acreage planted here is assumed to be a predetermined variable and input decisions are restricted to nitrogen and phosphorus application rates. Nitrogen and phosphorus application rates are obtained on a state-by-state basis in USDA's Agricultural Resources: Situation and Outlook Report and in Fertilizer Use and Price Statistics, 1960-85 (Vroomen, 1987).

Information on Oregon input prices at the state level are given in Agricultural Prices - Summary (annual reports).

Heteroskedastic Production Functions

For the study of Iowa corn production, multiplicative (Cobb-Douglas) functional forms are employed for f(x) and h(x). The specific production functional form using the above five inputs is

$$y = AN^{a1}H^{a2}K^{a3}S^{a4}L^{a5} + BN^{b1}H^{b2}K^{b3}e \tag{17}$$

where N is nitrogen, H is phosphorus, K is potassium, S is ground slope, and L is soil clay content. S and L are not included in the variance portion h(x) because slope and clay content are assumed not to affect corn yield variability. Dividing through by $N^{b1}H^{b2}K^{b3}$ gives the homoskedastic form of (17):

$$(y - AN^{a1}H^{a2}K^{a3}S^{a4}L^{a5})/(N^{b1}H^{b2}K^{b3}) = Be \tag{18}$$

Employing (17), per-acre profit is

$$\begin{aligned} W &= Py - r_1N - r_2H - r_3K \\ &= PAN^{a1}H^{a2}K^{a3}S^{a4}L^{a5} + PBN^{b1}H^{b2}K^{b3}e - r_1N - r_2H - r_3K \end{aligned} \tag{19}$$

From equation (19)

$$\begin{aligned} E(W) &= PAN^{a1}H^{a2}K^{a3}S^{a4}L^{a5} - r_1N - r_2H - r_3K \\ \sigma^2(W) &= P^2B^2N^{2b1}H^{2b2}K^{2b3} \end{aligned}$$

and profit standard deviation is

$$\sigma(W) = PBN^{b1}H^{b2}K^{b3}$$

The farmer is assumed generally non-neutral toward risk with negative exponential utility $U(W) = -\exp(-\lambda W)$, where $\lambda = U''(W)/U'(W)$ is absolute risk aversion. Note that in $-\exp(-\lambda W)$, absolute risk aversion is a constant with respect to W.

Following equation (5), optimal input demands are found by

$$\text{Max } E[U(W)] = \text{Max } E[U(PAN^{a1}H^{a2}K^{a3}S^{a4}L^{a5} + PBN^{b1}H^{b2}K^{b3}e - r_1N - r_2H - r_3K)].$$

Deriving first-order conditions with respect to each input N, H, and K gives, following equation (6),

$$E\{U'(W)[PAa_1N^{a1-1}H^{a2}K^{a3}S^{a4}L^{a5} + PBb_1N^{b1-1}H^{b2}K^{b3}e - r_1]\} = 0$$
$$E\{U'(W)[PAa_2N^{a1}H^{a2-1}K^{a3}S^{a4}L^{a5} + PBb_2N^{b1}H^{b2-1}K^{b3}e - r_2]\} = 0$$
$$E\{U'(W)[PAa_3N^{a1}H^{a2}K^{a3-1}S^{a4}L^{a5} + PBb_3N^{b1}H^{b2}K^{b3-1}e - r_3]\} = 0.$$

Reordering and dividing through by $E[U'(W)]$ gives

$$\begin{aligned} PAa_1N^{a1-1}H^{a2}K^{a3}S^{a4}L^{a5} + PBb_1N^{b1-1}H^{b2}K^{b3}t &= r_1 \\ PAa_2N^{a1}H^{a2-1}K^{a3}S^{a4}L^{a5} + PBb_2N^{b1}H^{b2-1}K^{b3}t &= r_2 \\ PAa_3N^{a1}H^{a2}K^{a3-1}S^{a4}L^{a5} + PBb_3N^{b1}H^{b2}K^{b3-1}t &= r_3. \end{aligned} \tag{20}$$

where $t = E[U'(W)e]/E[U'(W)]$.

Consider now the evaluation of term t. If profit is expressed as $W = \mu + \sigma e$, where μ is profit's mean and σ is its standard deviation, expected utility is

$$E[U(W)] = -E[\exp(-\lambda\mu - \lambda\sigma e)].$$

This is the negative of the expectation of a log normally distributed variable with parameters $-\lambda\mu$, $\lambda^2\sigma^2$. Johnson and Kotz (1970) show that the mean of a log normally distributed variable x is

$$E(x) = E[\exp(-\lambda\mu - \lambda\sigma e)] = \exp(-\lambda\mu + \lambda^2\sigma^2/2). \tag{21}$$

To calculate the denominator of t, take the expectation of the derivative of expected utility with respect to profit:

$$\begin{aligned} E[U'(W)] &= -E[d\exp(-\lambda W)/dW] = \lambda E[\exp(-\lambda W)] \\ &= \lambda E[\exp(-\lambda\mu - \lambda\sigma e)]. \end{aligned} \tag{22}$$

Substituting (21) into (22) implies the denominator of t is $\lambda\exp(-\lambda\mu + \lambda^2\sigma^2)$. Therefore,

$$E[u'(W)] = \lambda\exp(-\lambda\mu + \lambda^2\sigma^2/2). \tag{23}$$

To calculate numerator of t, follow a similar procedure. Note that

$$\begin{aligned} E[U'(W)e] &= -E[d\exp(-\lambda W)e/dW] = \lambda E[\exp(-\lambda W)e] \\ &= \lambda E[\exp(-\lambda\mu - \lambda\sigma e)e]. \end{aligned}$$

Now the expected value of log normally distributed variable $E[\exp(a + be)e] = b\exp(a + b^2/2)$. Since $a = -\lambda\mu$ and $b = -\lambda\sigma$ here, we have

$$E[\exp(-\lambda\mu - \lambda\sigma e)e] = -\lambda\sigma\exp(-\lambda\mu + \lambda^2\sigma^2/2).$$

Therefore,

$$E[u'(W)e] = \lambda E[(-\lambda\mu - \lambda\sigma e)e] = -\lambda^2\sigma\exp(-\lambda\mu + \lambda^2\sigma^2/2) \tag{24}$$

Taking the ratio (24) to (23), we then have

$$t = E[U'(W)e]/E[U'(W)]$$
$$= [-\lambda^2\sigma\exp(-\lambda\mu + \lambda^2\sigma^2)]/[\lambda\exp(-\lambda\mu + \lambda^2\sigma^2)] = -\lambda\sigma.$$

From equation (19) also, the standard deviation of profit is $\sigma = PBN^{b1}H^{b2}K^{b3}$. Substituting this into (24) gives

$$t = -\lambda\sigma = -\lambda PBN^{b1}H^{b2}K^{b3} \qquad (25)$$

Substituting (25) into the input demand equations (20) gives, finally,

$$\begin{aligned} &PAa_1N^{a1-1}H^{a2}K^{a3}S^{a4}L^{a5} - \lambda P^2B^2b_1N^{2b1-1}H^2b^2K^{2b3} = r_1 \\ &PAa_2N^{a1}H^{a2-1}K^{a3}S^{a4}L^{a5} - \lambda P^2B^2b_2N^{2b1}H^{2b2-1}K^{2b3} = r_2 \\ &PAa_3N^{a1}H^{a2}K^{a3-1}S^{a4}L^{a5} - \lambda P^2B^2b_3N^{2b1}H^{2b2}K^{2b3-1} = r_3. \end{aligned} \qquad (26)$$

To allow estimation of the parameters in (26), add normally distributed random error terms u_1, u_2, and u_3. These residuals represent optimization error. Assuming choices are optimal on average, the distribution of the input demands is $u_1 \sim N(0, s_1^2)$, $u_2 \sim N(0,s_2^2)$, and $u_3 \sim N(0,s_3^2)$. Observe that production function (18) can be assumed to have homoskedastic error $Be \sim N(0,B^2)$. Thus, input demands (26) and production function (18) can be estimated jointly once a covariance structure for the errors (u_1, u_2, u_3, Be) has been established.

Input demand equations (26) differ from the neoclassical ones by the addition of the second term of the left-hand side in each equation. The first term of each left-hand side gives the marginal change in expected revenue caused by a unit change in the respective input. The second term of each left-hand side gives the associated marginal risk premium. This may be seen as follows. As indicated before, Pratt shows the risk premium of a risky prospect is approximately is $r\sigma^2/2$, where r is the coefficient of absolute risk aversion. For the exponential utility form here, the risk coefficient $r = \lambda$. Hence the risk premium is

$$RP = \lambda\sigma^2/2 = \lambda P^2B^2N^{2b1}H^{2b2}K^{2b3}/2.$$

Taking the derivative of RP with respect to inputs N, H, and K gives the marginal risk premia

$$dRP/dN = \lambda P^2B^2b_1N^{2b1-1}H^2b^2K^{2b3}$$
$$dRP/dH = \lambda P^2B^2b_2N^{2b1}H^{2b2-1}K^{2b3}$$
$$dRP/dK = \lambda P^2B^2b_3N^{2b1}H^{2b2}K^{2b3-1}$$

which are identical to the second left-hand side terms in equation (26). These terms indicate the marginal changes in the risk premium caused by increasing one unit of each respective input. Finally, the right-hand sides of (26) give the marginal market costs of each input caused by increasing the use of that input by one unit. Hence, equation (26) says optimal input use occurs where expected marginal revenue less marginal risk premium or cost equals marginal market cost of each input. In the case of perfectly competitive input markets, marginal market cost is just input price.

For the study of Oregon wheat production, quadratic functional forms are used for f(x) and linear functional forms for h(x). The reason for the quadratic and linear functional forms is that the multiplicative forms do not give converging estimated coefficients in the systems approach. Input variables modelled in the Oregon study include nitrogen, phosphorus, and acres planted. Hence, the specific function estimated is

$$y = a_0 + a_1N + a_2N^2 + a_3H + a_4H + a_5R + a_6R^2 + (b_0 + b_1N + b_2H + b_3R)e \quad (27)$$

where N is nitrogen, H is phosphorus, and R is acreage planted. Potassium is not included among the input variables because too many observations of this variable were missing from the published data source. Dividing production function (27) by $b_0 + b_1N + b_2H + b_3R$ gives the homoskedastic form

$$(y - (a_0 + a_1N + a_2N^2 + a_3H + a_4H^2 + a_5R + a_6R^2))/(b_0 + b_1N + b_2H + b_3R) = e \quad (28)$$

In the short run, it was assumed planted acreage has no market. Hence there is no price for land and per-acre profit becomes

$$\begin{aligned} W &= Py - r_1N - r_2H \\ &= P(a_0 + a_1N + a_2N^2 + a_3H + a_4H^2 + a_5R + a_6R^2) \\ &\quad + P(b_0 + b_1N + b_2H + b_3R)e - r_1N - r_2H \end{aligned} \quad (29)$$

From equation (29), expectation and variance of profit are

$$E(W) = P(a_0 + a_1N + a_2N^2 + a_3H + a_4H^2 + a_5R + a_6R^2) - r_1N - r_2H$$

$$\sigma^2(W) = P^2(b_0 + b_1N + b_2H + b_3R)^2$$

and profit standard deviation is

$$\sigma(W) = P(b_0 + b_1N + b_2H + b_3R).$$

As in the Iowa study, the farmer is assumed non-neutral toward risk with negative exponential utility $U(W) = -\exp(-\lambda W)$, where λ is absolute risk aversion. The farmer's objective is to maximize his expected utility, that is,

$$\max E[U(W)] = E\{U[P(a_0 + a_1N + a_2N^2 + a_3H + a_4H^2 + a_5R + a_6R^2) + P(b_0 + b_1N + b_2H + b_3R)e - r_1N - r_2H]\}$$

To find optimal input demands for Oregon wheat, derive first-order conditions with respect to the inputs N and H. That is,

$$E\{U'(W)[P(a_1 + 2a_2N) + Pb_1e - r_1]\} = 0$$
$$E\{U'(W)[P(a_3 + 2a_4H) + Pb_2e - r_2]\} = 0$$

Reordering and dividing through by $E[U'(W)]$ gives

$$\begin{aligned} &Pa_1 + 2Pa_2N + Pb_1t = r_1 \\ &Pa_3 + 2Pa_4H + Pb_2t = r_2 \end{aligned} \tag{30}$$

where $t=E[U'(W)e]/E[U'(W)]$.

Again as in the Iowa study,

$$t = -\lambda\sigma \tag{31}$$

where $\sigma = P(b_0 + b_1N + b_2H + b_3R)$.

Substituting (31) into the input demand equations (30) gives

$$\begin{aligned} &Pa_1 + 2Pa_2N - \lambda P^2b_1(b_0 + b_1N + b_2H + b_3R) = r_1 \\ &Pa_3 + 2Pa_4H - \lambda P^2b_2(b_0 + b_1N + b_2H + b_3R) = r_2 \end{aligned} \tag{32}$$

The second term in the left-hand side of each equation in (32) gives the respective marginal risk premium, that is, the marginal change in the risk premium caused by increasing one unit of each input N and H.

To allow estimation of the coefficients in (32), add normally distributed error terms u_1 and u_2. These residuals represent optimization errors. Assuming choices are optimal on the average, the distributions of the input demands for N and H are $u_1 \sim N(0,s_1^2)$ and $u_2 \sim N(0,s_2^2)$. Since production function (28) has homoskedastic $e \sim N(0,1)$, input demands (32) and production function (28) can be estimated jointly once a covariance structure for the errors (u_1, u_2, e) has been established.

Estimation Procedures

To conduct the Just-Pope-type analysis for Iowa counties, coefficients of f(x) were derived by applying nonlinear least square (NLS) estimation to obtain the first stage estimates of A and the a_i's in (17),

$$y = AN^{a1}H^{a2}K^{a3}S^{a4}L^{a5} + u \tag{33}$$

where $u = BN^{b1}H^{b2}K^{b3}e$. To derive the first stage estimates of B and the b_i's, the log of the absolute value of residual u was taken and regressed against $\log|BN^{b1}H^{b2}K^{b3}e|$. That is,

$$\log|u| = \log B + b_1\log N + b_2\log H + b_3\log K + \log|e|. \tag{34}$$

Second-stage estimates of coefficient of A and the a_i's then were obtained by applying NLS to the weighted regression in which estimates of b_1, b_2, and b_3 are used as parameters in production function (18). Estimates of B and the b_i's subsequently are derived by the same procedure as in the first stage, except that the second stage estimates of a_1, a_2, a_3, a_4, and a_5 are used instead of the first-stage estimates.

Observe that $\log|e|$ in (34) has an expected value of -0.6352 (Buccola and McCarl, 1986). Hence our estimate of logB in (34) is biased. To get an unbiased estimate of B, simply add 0.6352 to the negatively biased estimate of logB, then take the exponential of that to give $B^{\wedge} = \exp(\log B + 0.6352)$.

The following procedures were used to estimate the coefficients of f(x) and h(x) in the Just-Pope-type analysis for the Oregon county. Coefficients of f(x) are derived by applying nonlinear least squares to obtain the first stage estimates of the a_i's in (27),

$$y = a_0 + a_1N + a_2N^2 + a_3H + a_4H^2 + a_5R + a_6R^2 + u$$

where $u = b_0(b_1N + b_2H + b_3R)e$. To obtain the first-stage estimates of the b_i's, take the log of the absolute value of residual $u = (b_0 + b_1N + b_2H + b_3R)e$. That is,

$$\begin{aligned} \log|u| &= \log|e| + \log(b_0 + b_1N + b_2H + b_3R) \\ &= -.6352 + \log(b_0 + b_1N + b_2H + b_3R). \end{aligned}$$

Second-stage estimates of the a_i coefficients are obtained by applying NLS to the weighted regression using production function (28). Subsequent estimates of the b_i's in this second stage are derived by the same procedure as in the first stage, except that the second stage estimates of a_1, a_2, a_3, a_4, a_5, and a_6 are used instead of the first-stage estimates.

The coefficients estimated using the Just-Pope method provide not only information for comparison with the systems estimates, but a set of starting values for the systems estimates as well. Any estimate of production function (17) assumes fertilizer input levels are exogenous. However, the optimization theory outlined above suggests these inputs are endogenous since they respond to changes in output price and fertilizer prices. In order to capture this endogeneity, the input demands need to be estimated as a system. In the following, 3SLS was used to estimate input demands (26) together with homoskedastic production function (18) for the Iowa data. Similarly, input demands (32) were used together with homoskedastic production function (28) for the Oregon data. Cross equation restrictions are employed to ensure that parameters in the production function equal the corresponding ones in the input demands.

Provided the production function parameters are indeed equal to those which appear in the input demands, the systems estimation is more efficient from that of OLS. The reason is that input levels in (26) and (32) are determined simultaneously. Simultaneity arises because relative input levels affect yield variance differently from the way they affect yield mean; both effects must be considered when determining the optimal input allocation. Simultaneity of the input demands is made clear from the fact that no closed-form expression for any input demand is possible in (26) and (32). Three stage least squares (3SLS) estimation uses all the information contained in a system of equations. Hence 3SLS estimation is efficient compared to OLS estimation because in 3SLS optimal levels of input usage are determined simultaneously.

The reasons why production functions (18) and (28) are involved in the system of equations are the following. First, one can compare the technology coefficients assumed by the producer in the course of his optimization, that is, in the course of input choice, with the technology coefficients actually estimated in the input-output relation. Second, including production functions (18) and (28) gives more information about actual output and input relations and so improves efficiency of estimation compared to the use of the input demands alone. Third, involving (18) and (28) helps to identify separately the λ and B terms in the input demand functions (26) and (32).

To employ 3SLS, operate as follows: First, obtain a transformation of model (26) and (18) for the Iowa counties and (32) and (28) for the Oregon county by using instrumental variables. The instrumental variables should not be correlated with the error terms but should be highly correlated with the explanatory variables. The number of instrumental variables required equals the number of coefficients to be estimated (Wonnacott and Wonnacott, 1979). Therefore, in the Iowa study, ten instrumental variables were used: expected corn price, ground slope, soil clay content, the dummy variables (nitrogen-fixing crop planted one or two years ago), the constant term, and prices of nitrogen, phosphorus, and potassium. Soybean production is competitive with or in some cases complementary to corn production, so that soybean prices ought to affect corn yields. Hence, the soybean price expectation is also used as an instrumental variable. This expectation is represented by the soybean futures price, which is modelled in the same manner as the futures price expectation for corn.

For the Oregon study, five instrumental variables were used. They were the constant term, wheat price, nitrogen price, phosphorus price and land.

The second step in employing 3SLS is to obtain a residual variance-covariance matrix by applying two-stage least squares (2SLS) estimation to (26) and (18), and (32) and (28). Third, generalized least squares (GLS) were used along with the estimated variance-covariance matrix to obtain the corresponding three-stage least squares estimates.

For the Iowa counties, f(x) and h(x) have a multiplicative form and we apply a nonlinear 3SLS estimator by using the Gauss-Newton algorithm (Judge et al., 1988; Hall et al., 1987). Each nonlinear set of 3SLS estimates of (18) and (26) is derived holding λ and B fixed at trial values. A grid search then is conducted about alternative λ values. The estimated coefficient set which minimizes system sum square errors was chosen as the optimal set. One cannot estimate λ and B simultaneously. To get a consistent estimate of B in the systems approach, substitute A, the a_i's, and the b_i's back into equation (33), take the log of absolute value of residual u, and regress it against $\log|BN^{b1}H^{b2}K^{b3}e|$. The estimated intercept of this regression, logB, is biased. To get a unbiased estimate of B, simply add 0.6352 to the negatively biased estimate of logB, then take the exponential of that to give $B^{\wedge}$ = exp(logB + 0.6352). To obtain a consistent estimate of λ, employ the λB^2 which minimized system sum square errors and divide this by the consistent estimate of B. Antle (1987) and Hazell (1982) proposed instead a model of risk preference estimation which allows different risk attitudes among a producer population.

For the Oregon counties, estimation of nonlinear 3SLS also is conducted with holding λ fixed at trial values. A grid search then is continued about alternative λ values and the coefficient set chosen which minimizes system sum square errors.

The Just-Pope method assumes the variables in the right-hand side of (17) and (27)--nitrogen, phosphorus, and potassium use, ground slope, soil clay content, and acreage levels--are exogenous variables. In the systems approach, on the other hand, input use is determined by input prices through the input demands. Further, input uses are simultaneously determined through the system of input demand equations (26). These two approaches therefore are inconsistent with one another. If the fertilizer usages are decided simultaneously, they cannot be independent variables. The Hausman specification test was used in conjunction with the Iowa data (Hausman, 1978 and 1981; White, 1982a and b) to test whether there exists simultaneity in the system of fertilizer demands.

The Hausman specification tests the null hypothesis of no simultaneity by contrasting the covariance matrix of an efficient estimator with an inefficient but generally consistent estimator under the alternative hypothesis of simultaneity. Using the Just-Pope method as the efficient estimator and the systems approach as the estimator which is consistent to test whether the instrumental variables are valid or not. To apply the test, a set of coefficients a_i of the mean portion are obtained using the Just-Pope method; an alternative set is obtained using the above method of instrumental variables. The test is computed by getting a set of parameter estimates with differences between the consistent estimates and the efficient estimates and also the matrix of differences by subtracting the covariance matrix with the efficient estimates from the covariance matrix with the consistent estimates. The quadratic form computed in this way has chi-square distribution with degrees of freedom equal to the number of parameters being tested. Instrumental variables employed for this purpose were the constant term, nitrogen price, phosphorus price, potassium price, ground slope, and soil clay content.

CHAPTER IV

RESULTS

Just-Pope parameter estimates of the aggregate production function for Fayette, Linn, and Muscatine Counties are shown in the left-hand columns of Tables 1-3. Parameter estimates for the systems approach appear in the right-hand columns of these tables. The dummy variables reflecting earlier presence of nitrogen-fixing crops are dropped because of insignificance in the regressions. In the case of the systems estimates, a wide range of absolute risk aversion coefficients λ were tried in each county. The optimal λ value in each case lied in the positive range. Production function coefficients A, a_i, and b_i were not very sensitive to these alternative absolute risk aversion levels.

Results of coefficient estimates of wheat production for Crook County, Oregon, are shown in Table 12. Parameters estimated using the Just-Pope method are at the left-hand side and parameters estimated from the systems model are at the right-hand side of the table. A wide range of values of λ were tried in order to minimize the sum of squared errors in the Oregon systems estimation. The optimal value of λ lies in the positive range for Crook County. As in the Iowa study, wheat production function coefficients A, a_i, B, and b_i are not much sensitive in the NL3SLS estimation to the alternative absolute risk aversion levels.

Table 1. Corn Yield Mean and Standard Deviation as Influenced by Selected Inputs, Fayette County, Iowa, 1964 - 1969.

Input	Just-Pope Method	Systems Method
-Yield Mean-		
Constant (A)	43.32 (3.45)	39.78 (1.89)
Nitrogen (N)	0.10 (3.70)	0.23 (3.65)
Phosphorus (H)	-0.07 (-1.14)	0.27 (1.92)
Potassium (K)	0.07 (1.66)	-0.24 (-1.19)
Slope (S)	-0.03 (-1.21)	0.07 (1.56)
Clay (L)	0.20 (2.40)	0.01 (0.14)
-Yield Standard Deviation-		
Constant (B)	61.97	2.03
Nitrogen (N)	-0.16 (-1.40)	0.41 (3.38)
Phosphorus (H)	-0.86 (-2.56)	0.23 (2.36)
Potassium (K)	0.72 (2.64)	0.06 (0.36)

Notes:

i) Numbers in parentheses are t-values. Sample size is 106.

ii) Yield is measured in bushels per acre and fertilizers in lbs. per acre. Sample means were N = 76.7, H = 52.1, K = 57.5, Slope = 4.2, Clay Content = 21.4, and Yield = 113.3. $\lambda = 0.14$.

Table 2. Corn Yield Mean and Standard Deviation as Influenced by Selected Inputs, Linn County, Iowa, 1964 - 1969.

Input	Just-Pope Method	Systems Method
-Yield Mean-		
Constant (A)	48.85 (3.89)	40.36 (4.19)
Nitrogen (N)	0.05 (2.40)	0.02 (1.41)
Phosphorus (H)	-0.01 (-1.61)	0.07 (2.05)
Potassium (K)	0.05 (0.91)	0.03 (1.90)
Slope (S)	0.04 (1.14)	0.07 (1.97)
Clay (L)	0.18 (2.87)	0.21 (4.20)
-Yield Standard Deviation-		
Constant (B)	4.87	0.21
Nitrogen (N)	0.06 (0.59)	0.09 (1.64)
Phosphorus (H)	0.56 (1.71)	0.80 (6.67)
Potassium (K)	-0.22 (-0.84)	0.35 (4.12)

Notes:

i) Numbers in parentheses are t-values. Sample size is 103.

ii) Yield is measured in bushels per acre and fertilizers in lbs. per acre. Sample means were N = 83.1, H = 50.1, K = 48.8, Slope = 3.3, Clay Content = 22.1, and Yield = 122.7. $\lambda = 0.016$

Table 3. Corn Yield Mean and Standard Deviation as Influenced by Selected Inputs, Muscatine County, Iowa, 1964 - 1969.

Input	Just-Pope Method	Systems Method
-Yield Mean-		
Constant (A)	46.90 (3.54)	26.32 (2.97)
Nitrogen (N)	0.10 (2.73)	0.12 (2.68)
Phosphorus (H)	-0.0003(-0.003)	0.05 (0.56)
Potassium (K)	0.01 (0.16)	0.01 (0.24)
Slope (S)	-0.09 (-3.41)	-0.06 (-1.40)
Clay (L)	0.20 (2.63)	0.30 (3.18)
-Yield Standard Deviation-		
Constant (B)	17.40	1.35
Nitrogen (N)	-0.26 (-2.01)	0.44 (5.33)
Phosphorus (H)	-0.16 (-0.36)	0.15 (1.70)
Potassium (K)	0.56 (1.83)	0.01 (0.48)

Notes:

i) Numbers in parentheses are t-values. Sample size is 55.

ii) Yield is measured in bushels per acre and fertilizers in lbs. per acre. Sample means were N = 98.5, H = 43.5, K = 34.2, Slope = 3.5, Clay Content = 23.4, and Yield = 126.2. $\lambda = 0.538$.

Parameter Analysis: Iowa

For the yield mean analysis in Fayette County, the test statistic for nitrogen is highly significant using both the Just-Pope and systems methods. When systems estimation is used, the elasticity of nitrogen (0.23) is more than twice the comparable figure in the Just-Pope method. For phosphorus and potassium, the Just-Pope and systems estimation give different signs, even though they are not significant statistically. Phosphorus under the Just-Pope method has a negative effect on yield mean, while potassium under the systems method has a negative effect on yield mean. The clay content test statistic is significant using the Just-Pope method, showing an elasticity of 0.20. This implies that a ten percent increase in clay will increase mean corn yield by two percent. At the same time, both production functions show strongly decreasing returns to scale insofar as the coefficients sum to a constant much less than one.

In the variance analysis for Fayette County, there were significant differences between the two methods. Using the Just-Pope method, nitrogen and phosphorus have the effect of reducing yield risk, while in the systems estimation they have an increasing effect on yield risk. Nitrogen under the systems method plays the most important role in yield variance, followed by phosphorus. In the Just-Pope method, on the contrary, phosphorus has the greatest impact on yield risk. Phosphorus has an elasticity here of -0.86, implying a ten percent increase in phosphorus use reduces yield standard deviation by 8.6 percent. Potassium was the only input to increase yield risk in the Just-Pope framework.

In the yield mean analysis for Linn County, there is little difference between the two methods' results, with the exception of phosphorus. With the Just-Pope method, nitrogen is significant and has an increasing effect on the yield mean, whereas phosphorus has a decreasing effect that is not statistically significant. With systems estimation, both phosphorus and nitrogen have a positive effect on corn yield mean. Both the Just-Pope and the systems estimates indicated clay content has the most important effect on yield mean, followed by nitrogen and potassium in the Just-Pope method and phosphorus and slope in the systems method.

In the analysis of yield variance in Linn County, there were substantial differences between the two methods except for nitrogen. With the Just-Pope method, phosphorus was more important than nitrogen in increasing variability of corn yield, and potassium was the only factor reducing the variability of corn yield. But none of these effects are significant statistically. In the systems estimation, phosphorus and potassium were highly significant. The systems estimates showed phosphorus had the most important role in yield variability with an elasticity of 0.80, implying a ten percent increase in phosphorus use increases yield standard deviation by eight percent.

In the yield mean analysis for Muscatine County, results were similar regardless of method except in the case of clay content. With the Just-Pope method, nitrogen, ground slope, and clay content were significant statistically. The Just-Pope-type estimates showed clay content had the most important role in increasing yield mean, followed by nitrogen and potassium. Ground slope in the Just-Pope method had a decreasing effect on yield mean with an elasticity of -0.09, implying a ten percent increase in slope decreases yield mean by 0.9 percent. With the systems estimation, clay and nitrogen were factors in increasing yield mean and they are also significant statistically. But phosphorus was not a significant factor in either method.

In the analysis of yield variance for Muscatine County, there were substantial differences between the two methods. Nitrogen was significant statistically in each method. Nitrogen in the Just-Pope method served to reduce variability of output, in contrast to the increasing effect on variability of output that nitrogen had in the systems estimation. Phosphorus and potassium were nonsignificant in both methods. In the Just-Pope method, potassium was the major variable influencing yield variability. In the systems estimation, the major variable instead was nitrogen.

Parameter Analysis: Oregon

For the analysis of yield mean in Crook County, there also were substantial differences between the two methods. With the Just-Pope method, phosphorus and the squared term on nitrogen were highly significant statistically, while all systems estimates were nonsignificant. The Just-Pope estimates indicated phosphorus had the most important role in increasing wheat yield expectation. Its marginal productivity at the sample mean (5.7 lbs.) was 35.11 bushels per acre, implying an additional one pound of phosphorus use increases wheat yield by 35.11 bushels.

In the system estimates, both the linear and squared terms for phosphorus had a positive effect on wheat production, although they were not significant statistically. The marginal productivity of a pound of phosphorus at the sample mean was 0.88 bushels of wheat per acre.

Nitrogen coefficients using the Just-Pope method were larger than those in the systems estimation. The Just-Pope-type estimates showed nitrogen's marginal productivity at sample mean (54.2 lbs.) was -31.98 bushels per acre and the systems method showed it was -4.336 bushels per acre, implying an additional pound of nitrogen use decreases wheat yield by 4.336 bushels.

The analysis of land usage using the systems method was very different from that using Just-Pope analysis. Linear terms in the Just-Pope method showed a positive effect on wheat yield mean, whereas the systems method showed a negative effect on yield mean. With the Just-Pope method, acres cultivated had a positive effect on wheat production; the marginal productivity of 1,000 acres at the sample mean (3,000 acres) was 10.77 bushels. With the systems method, on the other hand, acres had a decreasing effect on yield mean: marginal productivity was -491.38, implying an additional 1,000 acres in land use decreased wheat yield by 491.38 bushels.

In the analysis of wheat yield variance in Crook County, the results of the two methods also appear to be substantially different. With the Just-Pope method, land usage had the greatest positive impact on yield risk and was significant statistically. Phosphorus and nitrogen had decreasing effects on yield risk. Conversely in the systems estimation, acres cultivated was the only factor decreasing yield risk, while phosphorus and nitrogen increased yield risk. Phosphorus was significant statistically under the systems method, with a slope of 0.06. This implies an additional one pound of phosphorus increases yield standard deviation by 0.06 bushels per acre.

Substituting coefficients A, a_i, and b_i obtained with the systems estimation into equation (18) and adding 0.6352 to the mean log of $|Be|$ results in B estimates of 2.03, 0.21, and 1.35, respectively, for Fayette, Linn, and Muscatine Counties. These consistent B estimates were used to calculate the coefficients of absolute risk aversion, λ, for these counties. Dividing our NL3SLS estimates of λB^2 by the square of the respective consistent B estimate gave λ estimates of 0.140, 0.016, and 0.538, respectively. All of these imply the average farmer is risk averse.

In the analysis of Crook County, the consistent estimate of B was simultaneously estimated with the A, a_i, and b_i parameters for alternative values of λ. A grid search was then conducted on the λs to minimize sum square errors. The estimated value of B was - 0.55 and the estimated value of λ was 0.75. Again, this implies the average farmer is risk averse.

Crook County farmers produce wheat as part of a crop rotation. However, their wheat production amounts to less than 0.5 percent of total Oregon volume and constitutes less than 20 percent of their own income. Given that wheat generates a small percentage of their income, farmers may exhibit less risk averse behavior in wheat production than they would if the wheat share of their income were higher.

Hausman Specification Test

The Hausman specification test was conducted for Linn, Muscatine, and Fayette Counties to test the existence of simultaneity in the systems of fertilizer demands. When the asymptotic variance of the efficient estimate is greater than that of the consistent estimate, some diagonal elements may be negative. The test then computes only for those parameters corresponding to positive diagonal elements, with a corresponding correction to the degrees of freedom. The test statistics for Fayette, Linn, and Muscatine Counties were, respectively, 3.05, 6.52, and 2.39 with five degrees of freedom in each county. The critical value at five degrees of freedom and a five percent significant level is 11.07. Hence, these test statistics failed to reject the null hypothesis of no simultaneity in the systems of fertilizer demand equations.

Alternative instrumental variable sets were used to find whether the null hypothesis was rejected or not. Instrumental variables employed for Iowa counties were: 1) nitrogen price, phosphorus price, potassium price, ground slope, soil clay content, soybean price, a constant term, and a dummy variable for a nitrogen fixing crop planted two years previously; 2) nitrogen price, phosphorus price, potassium price, ground slope, soil clay content, soybean price, a constant term, and dummy variables for nitrogen fixing crops planted one and two years previously. The test statistics for Fayette, Linn, and Muscatine Counties in the first case were 7.26, 7.03, and 1.36 with 5, 6, and 4 degrees of freedom in each county, respectively. The critical value for 4 and 6 degree of freedom at five percent significant level are

9.49 and 12.59, respectively. Thus, the test statistics failed to reject the no simultaneity hypothesis in the systems of input demand equations. The test statistics for the three Iowa counties in the second case were 0.34, 2.14, and 1.80, respectively, all with 6 degrees of freedom. The test statistics in the second case also failed to reject the null hypothesis. Therefore, nitrogen, phosphorus, and potassium in Iowa counties are exogenous variables and the levels of these inputs are not determined simultaneously given the alternative instrumental variable sets.

Input Demand and Output Supply: Linn County

Once the system parameter estimates are known, they may be used to trace out the mean production function, output supply, and input demands for each county. For this purpose, the estimated production function and risk aversion coefficients were substituted into equations (26) and (17). For this purpose, the nonmarketable inputs, ground slope and soil clay content, were set at their sample means. Alternative output prices and own input price levels were then employed to calculate per-acre fertilizer demands. Finally, these demands were substituted into (1) along with the estimated coefficients to determine the mean and variance of supply at the given alternative output and input prices. To compare with the case of risk neutrality, risk aversion coefficients λ in some solutions were set at zero for each input price level. Since equation (26) is not expressible in explicit form, MathCAD 2.0 was used to obtain the input demand solutions given alternative price and parameter values.

The responses of fertilizer demand and expected corn supply to nitrogen price changes in Linn County are shown in Table 4. This table provides figures for the case of (a) risk neutrality and (b) the estimated absolute risk aversion of 0.016. The nitrogen demands for the risk neutral and risk averse producers are both negatively sloped. The risk averse demand, located in the left-hand columns of the table, are steeper in comparison to those for the case of risk neutrality. Price declines cannot raise nitrogen demand of the risk averter as much as of the risk neutral farmer since greater use of nitrogen generates more yield risk. Both the risk averse and risk neutral demands are lower than the sample mean nitrogen demand (83.1 lbs. per acre). Phosphorus and potassium demands in the risk neutral case decline with higher nitrogen price, implying phosphorus and potassium are complements to nitrogen. However, under risk aversion demand for phosphorus and potassium increases as the nitrogen price increases, implying that phosphorus and potassium are regarded as substitutes for nitrogen.

Fertilizer demands and expected corn supply at alternative phosphorus prices in Linn County are shown in Table 5. For both risk averse and risk neutral farmers, phosphorus demands are negatively sloped, although demand in the risk averse case is less elastic than in the risk neutral case. The relative inelasticity comes about because the high phosphorus coefficient in the yield variance portion of the production function implies yield risk rises with increased phosphorus use. The risk neutral farmer's demand for phosphorus is

Table 4. Nitrogen, Phosphorus, and Potassium Demand and Expected Corn Supply at Alternative Nitrogen Prices, Linn County, Iowa, 1964 - 1969.

Nitrogen Price	Nitrogen Demand $\lambda = 0$	Nitrogen Demand λ=0.016	Phosphorus Demand $\lambda = 0$	Phosphorus Demand λ=0.016
3.3	63.9	32.0	121.8	40.6
4.8	43.7	22.1	121.2	41.3
6.4	32.9	16.7	120.7	41.9
7.0	29.8	15.3	120.6	42.1
9.3	22.4	11.6	120.1	42.7

Nitrogen Price	Potassium Demand $\lambda = 0$	Potassium Demand λ=0.016	Expected Corn Supply $\lambda = 0$	Expected Corn Supply λ=0.016
3.3	109.8	26.4	139.8	123.4
4.8	109.2	27.2	139.2	123.2
6.4	108.8	27.9	138.7	123.0
7.0	108.7	28.1	138.5	122.9
9.3	108.3	28.7	138.0	122.8

Notes:

i) Fertilizer demands are in lbs per acre, corn supply is in bushels per acre, and nitrogen prices are in 1967 cents per lb.

ii) Corn price, phosphorus price, and potassium price are held fixed at $1.30 per bushel, 10.6 cents per lb., and 4.4 cents per lb., respectively (1967 dollars).

Table 5. Nitrogen, Phosphorus, and Potassium Demand and Expected Corn Supply at Alternative Phosphorus Prices, Linn County, Iowa, 1964 - 1969.

Phosphorus Price	Nitrogen Demand		Phosphorus Demand	
	λ = 0	λ=0.016	λ = 0	λ=0.016
9.0	33.4	16.2	144.8	45.8
9.5	33.2	16.3	136.6	44.5
10.6	32.9	16.7	120.7	41.9
11.0	32.8	16.8	116.6	41.1
11.5	32.7	17.0	111.1	40.1

	Potassium Demand		Expected Corn Supply	
	λ = 0	λ=0.016	λ = 0	λ=0.016
9.0	110.3	24.6	140.5	123.3
9.5	109.8	25.7	139.9	123.2
10.6	108.8	27.9	138.7	123.0
11.0	108.6	28.6	138.3	122.9
11.5	108.2	29.6	137.8	122.8

Notes:

i) Fertilizer demands are in lbs per acre, corn supply is in bushels per acre, and phosphorus prices are in 1967 cents per lb.

ii) Corn price, nitrogen price, and potassium price are held fixed at $1.30 per bushel, 6.4 cents per lb., and 4.4 cents per lb., respectively (1967 dollars).

higher than the sample mean (50.1 lbs. per acre), whereas the risk averse demands for phosphorus are quite near the sample mean use.

Nitrogen and potassium demands for the risk neutral case are negatively sloped, but nearly inelastic, with respect to phosphorus price changes. On the other hand, for the risk averter, nitrogen and potassium demands are positively sloped with respect to phosphorus price changes. In addition, potassium demand for the risk neutral farmer increases with higher phosphorus price, implying potassium is a substitute for phosphorus. Expected corn supplies for both the risk neutral and risk averse farmer are negatively sloped and inelastic.

Input demands and output supply responses to potassium price changes appear in Table 6. Potassium demand for the risk averter is steeper and to the left of that of the risk neutral farmer because increased potassium use caused by lower potassium prices is mitigated by the positive effect of potassium use on yield risk. Risk neutral nitrogen and phosphorus demands are negatively sloped and somewhat inelastic, whereas the risk averse demands are positively sloped and somewhat inelastic.

Fertilizer demands and corn supply responses to alternative corn prices for Linn County are shown in Table 7. Nitrogen demands for risk averse and risk neutral producers are both positively sloped. The risk averter's nitrogen demand is less elastic than and lies to the left of the risk neutral demand. The risk averter's inelastic nitrogen demand implies that increased nitrogen use increases profit risk more than it increases expected profit. Therefore, the risk averse producer would not increase nitrogen use as much as would the risk neutral producer.

Table 6. Nitrogen, Phosphorus, and Potassium Demand and Expected Corn Supply at Alternative Potassium Prices, Linn County, Iowa, 1964 - 1969.

Potassium Price	Nitrogen Demand		Phosphorus Demand	
	$\lambda = 0$	λ=0.016	$\lambda = 0$	λ=0.016
3.6	33.1	16.4	121.5	40.2
4.0	33.0	16.6	121.1	41.1
4.4	32.9	16.7	120.7	41.9
4.8	32.8	16.8	120.5	42.6
5.2	32.8	17.0	120.2	43.3
	Potassium Demand		**Expected Corn Supply**	
	$\lambda = 0$	λ=0.016	$\lambda = 0$	λ=0.016
3.6	134.6	31.9	139.5	123.0
4.0	120.8	29.7	139.1	123.0
4.4	108.8	27.9	138.7	123.0
4.8	100.1	26.3	138.3	122.9
5.2	92.2	24.9	138.0	122.9

Notes:

i) Fertilizer demands are in lbs per acre, corn supply is in bushels per acre, and potassium prices are in 1967 cents per lb.

ii) Corn price, nitrogen price, and phosphorus price are held fixed at $1.30 per bushel, 6.4 cents per lb., and 10.6 cents per lb., respectively (1967 dollars).

Table 7. Nitrogen, Phosphorus, and Potassium Demand and Expected Corn Supply at Alternative Corn Prices, Linn County, Iowa, 1964 - 1969.

Corn Price	Nitrogen Demand		Phosphorus Demand	
	$\lambda = 0$	λ=0.016	$\lambda = 0$	λ=0.016
0.70	16.4	12.2	60.1	39.3
1.00	24.4	14.8	89.7	41.7
1.30	32.9	16.7	120.7	41.9
1.60	41.4	18.8	152.0	41.6
1.90	50.3	20.8	184.4	41.5

	Potassium Demand		Expected Corn Supply	
	$\lambda = 0$	λ=0.016	$\lambda = 0$	λ=0.016
0.70	54.2	32.7	128.5	122.6
1.00	80.8	31.4	134.4	123.2
1.30	108.8	27.9	138.7	123.0
1.60	137.0	23.9	142.2	122.6
1.90	166.2	20.2	145.2	122.2

Notes:

i) Fertilizer demand are in lbs per acre, corn supply is in bushels per acre, and corn prices are in 1967 dollars per bushel.

ii) Nitrogen price, phosphorus price, and potassium price are held fixed at 6.4 cents, 10.6 cents, and 4.4 cents per lb., respectively (1967 dollars).

For the risk averter, phosphorus demand is nearly vertical and potassium demand is slightly negatively sloped. The reason for these inelasticities is that there will be more risk to both yields and profits with higher corn prices when the risk averter increases the use of phosphorus and potassium than when he increases the use of nitrogen. The corn supply curve for the risk neutral farmer is positively sloped and passes slightly to the right of the sample mean (122.7 bushel per acre). But the risk averse supply curve lies almost at the sample mean and is back bending: it is positively sloped up to a corn price of \$1.30 and negatively sloped above \$1.30. The reason for this slight negative slope is that the greater input use brought about by higher corn prices induces much higher yield risk and only slightly higher yield mean.

Input Demand and Output Supply: Muscatine County

For Muscatine County, fertilizer demands and corn supply at alternative fertilizer prices are shown in Tables 8-10. Impacts on fertilizer demand and corn supply of changes in corn price are shown in Table 11.

Own-price nitrogen demands for the risk neutral and risk averse producers are both negatively sloped, lying to the left and right, respectively, of the sample mean (98.5 lbs.). The risk averter's nitrogen demand is less sensitive than is the risk neutral demand to nitrogen price changes. Decreases in nitrogen price cannot substantially raise nitrogen demand for the risk averter since the greater nitrogen use causes a great deal more risk in yield. High risk aversion (λ = 0.538) and a large nitrogen coefficient (0.44) in the yield risk portion of the production function account for the large difference in nitrogen demand between the risk neutral and risk averse farmer.

For risk neutral farmers, there is a decrease in phosphorus and potassium demand as the price of nitrogen increases, implying that phosphorus and potassium are complementary to nitrogen. However, for the risk averse case, demand for phosphorus and potassium increases as nitrogen price increases. This implies that phosphorus and potassium are substitutes for nitrogen. In both the risk neutral and risk averse cases, expected corn supplies decrease as nitrogen prices increase, although the effect is less sensitive for the risk averter, since its fertilizer demand is also less sensitive to nitrogen prices. Expected corn supplies for the risk averse and risk neutral producer lie to the left and right, respectively, of the sample mean yield (126.2 bushels).

Table 9 indicates changes in input demands and output supply at alternative phosphorus prices. Nitrogen demand and corn supply follow the same general patterns as established in Table 8. Potassium demands for the risk neutral and risk averse farmer are both nearly vertical, implying that changes in potassium supply will not much affect potassium quantity demanded. The risk averter's relatively more inelastic phosphorus demand derives from the very high coefficients in the variance portion of the production function. Phosphorus demand for the risk neutral producer is far to the right of the sample mean use rate (43.5 lbs.), whereas phosphorus demand for the risk averter is to the left of sample mean.

Table 8. Nitrogen, Phosphorus, and Potassium Demand and Expected Corn Supply at Alternative Nitrogen Prices, Muscatine County, Iowa, 1964 - 1969.

Nitrogen Price	Nitrogen Demand		Phosphorus Demand	
	$\lambda = 0$	$\lambda=0.538$	$\lambda = 0$	$\lambda=0.538$
3.3	884.8	12.4	113.7	12.3
4.8	575.9	12.1	107.6	12.8
6.3	421.6	11.8	103.4	13.3
7.0	373.7	11.6	101.9	13.5
9.3	269.8	11.2	97.7	14.2

	Potassium Demand		Expected Corn Supply	
	$\lambda = 0$	$\lambda=0.538$	$\lambda = 0$	$\lambda=0.538$
3.3	55.3	21.6	187.2	99.4
4.8	52.4	21.6	177.2	99.4
6.3	50.3	21.7	170.3	99.2
7.0	49.5	21.7	167.7	99.1
9.3	47.5	21.8	160.8	98.9

Notes:

i) Fertilizer demand are in lbs per acre, corn supply is in bushels per acre, and nitrogen prices are in 1967 cents per lb.

ii) Corn price, phosphorus price, and potassium price are held fixed at $1.30 per bushel, 10.7 cents per lb., and 4.4 cents per lb., respectively (1967 dollars).

Table 9. Nitrogen, Phosphorus, and Potassium Demand and Expected Corn Supply at Alternative Phosphorus Prices, Muscatine County, Iowa, 1964 - 1969.

Phosphorus Price	Nitrogen Demand		Phosphorus Demand	
	$\lambda = 0$	$\lambda=0.538$	$\lambda = 0$	$\lambda=0.538$
9.0	426.1	11.2	124.3	15.7
9.5	424.7	11.3	117.4	14.9
10.7	421.6	11.8	103.4	13.3
11.0	420.9	11.8	100.4	13.0
11.5	419.8	12.0	95.8	12.4

	Potassium Demand		Expected Corn Supply	
	$\lambda = 0$	$\lambda=0.538$	$\lambda = 0$	$\lambda=0.538$
9.0	50.8	21.7	172.1	99.4
9.5	50.7	21.7	171.5	99.3
10.7	50.3	21.7	170.3	99.2
11.0	50.2	21.7	170.0	99.1
11.5	50.1	21.7	169.5	99.1

Notes:

i) Fertilizer demands are in lbs per acre, corn supply is in bushels per acre, and phosphorus prices are in 1967 cents per lb.

ii) Corn price, nitrogen price, and potassium price are held fixed at $1.30 per bushel, 6.4 cents per lb., and 4.4 cents per lb., respectively (1967 dollars).

Demand and supply responses at alternative potassium prices are indicated in Table 10. There is very little change in nitrogen and phosphorous demands or corn supplies for either the risk averter or risk neutral producer. Potassium demands in the risk neutral and risk averse situations are both negatively sloped. For the risk averter, potassium demand is to the left of the sample mean (34.2 lbs.), whereas the risk neutral demand is to the right of the sample mean. The reason for the risk averse farmer's potassium demand insensitivity is that increased potassium demand in response to lower prices is mitigated by the positive effect of potassium use on yield risk.

Input demand and output supply at alternative corn prices are shown in Table 11. For the risk neutral producer, both fertilizer demands and corn supply increase with higher corn prices. For the risk averse producer, nitrogen demand is negatively sloped, implying that profit risk increases with greater use of nitrogen, as well as with higher corn price. The risk averter's phosphorus demand is less price responsive than is that of the risk neutral farmer. Again, the insensitivity arises from the positive effect of phosphorus on yield risk.

For the risk averse producer, potassium demand is less inelastic than is phosphorus demand since potassium has a lower effect on yield risk than does phosphorus. Expected corn supply for the risk averter is negatively sloped with respect to corn prices. The reason for this negative slope is that even though nitrogen is the single most important fertilizer in increasing yield mean, it is also the most important in increasing yield standard deviation.

Table 10. Nitrogen, Phosphorus, and Potassium Demand and Expected Corn Supply at Alternative Potassium Prices, Muscatine County, Iowa, 1964 - 1969.

Potassium Price	Nitrogen Demand		Phosphorus Demand	
	$\lambda = 0$	$\lambda=0.538$	$\lambda = 0$	$\lambda=0.538$
3.6	422.7	11.7	103.7	13.3
4.0	422.1	11.7	103.6	13.3
4.4	421.6	11.8	103.4	13.3
4.8	421.2	11.8	103.3	13.3
5.2	420.8	11.8	103.2	13.3
	Potassium Demand		**Expected Corn Supply**	
	$\lambda = 0$	$\lambda=0.538$	$\lambda = 0$	$\lambda=0.538$
3.6	61.6	26.6	170.7	99.3
4.0	55.4	23.9	170.5	99.3
4.4	50.3	21.7	170.3	99.2
4.8	46.1	19.9	170.1	99.1
5.2	42.5	18.3	170.0	99.0

Notes:

i) Fertilizer demands are in lbs per acre, corn supply is in bushels per acre, and potassium prices are in 1967 cents per lb.

ii) Corn price, nitrogen price, and phosphorus price are held fixed at $1.30 per bushel, 6.4 cents per lb., and 10.7 cents per lb., respectively (1967 dollars).

Table 11. Nitrogen, Phosphorus, and Potassium Demand and Expected Corn Supply at Alternative Corn Prices, Muscatine County, Iowa, 1964 - 1969.

Corn Price	Nitrogen Demand		Phosphorus Demand	
	$\lambda = 0$	$\lambda=0.538$	$\lambda = 0$	$\lambda=0.538$
0.70	198.2	23.8	48.6	11.1
1.00	306.2	16.4	75.1	12.0
1.30	421.6	11.6	103.4	13.3
1.60	543.1	8.8	133.2	14.9
1.90	669.8	6.9	164.3	16.6
	Potassium Demand		**Expected Corn Supply**	
	$\lambda = 0$	$\lambda=0.538$	$\lambda = 0$	$\lambda=0.538$
0.70	23.6	13.1	148.6	106.4
1.00	36.5	17.5	160.7	102.4
1.30	50.3	21.7	170.3	99.2
1.60	64.8	25.8	178.2	96.5
1.90	79.9	29.8	185.1	94.3

Notes:

i) Fertilizer demands are in lbs per acre, corn supply is in bushels per acre, and corn prices are in 1967 dollars per bushel.

ii) Nitrogen price, phosphorus price, and potassium price are held fixed at 6.4 cents, 10.7 cents, and 4.4 cents per lb., respectively (1967 dollars).

Table 12. Wheat Yield Mean and Standard Deviation as Influenced by Selected Inputs, Crook County, Oregon, 1964 - 1987.

Input	Just-Pope Method	Systems Method
-Yield Mean-		
Constant (A)	33.62 (1.64)	307.37 (1.53)
Nitrogen (N)	-0.61 (-0.86)	-0.08 (-0.19)
Nitrogen (N^2)	0.01 (2.32)	0.003 (1.11)
Phosphorus (H)	7.84 (3.12)	0.15 (1.39)
Phosphorus (H^2)	-0.84 (-4.67)	0.004 (1.02)
Land (R)	1.87 (0.29)	-201.07 (-1.42)
Land (R^2)	0.86 (0.66)	37.27 (1.51)
-Yield Standard Deviation-		
Constant (B)	2.20 (0.78)	-0.55 (-1.23)
Nitrogen (N)	-0.06 (-0.52)	0.08 (1.06)
Phosphorus (H)	-1.33 (-1.39)	0.06 (2.12)
Land (R)	5.44 (2.86)	-0.75 (-1.05)

Notes:

i) Numbers in parentheses are t-values. Sample size is 24.

ii) Yield is measured in bushels per acre, fertilizers in lbs. per acre, and land in 1000 acre per unit. Sample means were N = 54.2, H = 5.7, R = 3, and Yield = 66.9. λ = 0.75.

Estimation of input demands and output supply also was attempted for Fayette County, but MathCAD did not provide convergent solutions. In addition, estimation of Crook County's offer curves was tried, but MathCAD generated negative phosphorus demands so these results are not reported.

CHAPTER V

CONCLUSIONS

Adding the element of risk to the production function complicates input demand and output supply analysis. Risk averters determine their input use levels after considering risk and their attitudes toward risk as well as after considering expectations.

Our data for Iowa counties reflect the behavior of individual farmers, whereas the Oregon data are a county aggregation of farmer behavior. With the systems approach, the Iowa data fit better to the optimal production function parameters than do the data from the Oregon counties. When the systems approach is applied to the Oregon counties, convergent NL3SLS results cannot be obtained with the exception of Crook County.

For the analysis of the Iowa counties, the Just-Pope and systems approaches show interesting results. Elasticities of yield mean estimated under the systems method are low and similar to those estimated under the Just-Pope method. However, elasticities of yield standard deviation for the Iowa counties differ substantially between the two approaches. All estimates in the systems approach show fertilizers with a positive influence on corn yield variance. Estimated risk aversion coefficients are all positive, consistent with the common assumption that farmers are risk averse. The magnitude of absolute risk aversion for Linn County is slight, but corresponding estimates for Fayette and Muscatine Counties are quite high according to Binswanger's characterization (Babcock et al., 1987)

In the analysis of Crook County, Oregon, systems estimates of yield mean and yield standard deviation are substantially different from those in the Just-Pope approach. Except for the phosphorus coefficient in the yield variance portion of the production function, all estimates using the systems method are nonsignificant. Estimated risk aversion for Crook County appears substantially high. Better production specification may improve the coefficient estimates of the systems method.

An advantage of the systems approach is that it includes producers' revealed opinions about production function relationships, including inputs' marginal effects on yield risk. Further, the systems approach can be used to derive estimates of absolute risk aversion that are consistent with these revealed opinions.

A disadvantage of the systems approach is that obtaining statistically optimal coefficient estimates is not an easy job. More than one locally optimal point often was obtained during the grid searches for the Iowa counties. Optimal coefficient estimates were sought for Jefferson, Marion, Wasco, Wheeler, and Yamhill Counties in Oregon, but convergent solutions were not found.

It was assumed that input demands and homoskedastic forms of the production functions have normally distributed errors. It was also assumed that producers have constant absolute risk aversion and that technology did not change during the course of the time series studied. Adoption of hybrid corn during the 1960s increased and stabilized yields. Fertilizer usage increased with these technological changes. Extending the scope of our model to include non-normally distributed errors, nonconstant risk aversion, or technology change would have made the systems approach more complicated.

This study has shown that input demand elasticities depend on the elasticities of yield mean and variance and on farmers' risk aversion. Inelastic per-acre corn supplies result from low elasticities of yield mean and high elasticities of yield variance even when risk aversion is moderate. This does not mean total corn supply is inelastic, since acreage may be significantly elastic. However, risk averse farmers respond rationally to high positive marginal risks by using rather fixed input proportions in the presence of changes in input and output prices.

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