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Estimating firm technical efficiency using alternative frontier function approaches: an application to farrow to finish hog production units

Leland C. Thompson

To the Graduate Council:

I am submitting herewith a dissertation written by Leland C. Thompson entitled "Estimating firm technical efficiency using alternative frontier function approaches: an application to farrow to finish hog production units." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Agricultural Economics.

Luther H. Keller, Major Professor

We have read this dissertation and recommend its acceptance:

S. Darrell Mundy, Ben R. McManus, Richard A. Hofler

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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ESTIMATING FIRM TECHNICAL EFFICIENCY USING ALTERNATIVE

FRONTIER FUNCTION APPROACHES: AN APPLICATION

TO FARROW TO FINISH HOG PRODUCTION UNITS

A Dissertation

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Leland C. Thompson

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ABSTRACT

The purpose of this study was to estimate the relative technical efficiency of individual farrow-to-finish swine production units and to analyze the relationship between firm technical efficiency and selected swine production practices. Study areas included 11 states in the North Central region and seven states in the Southeast region of the U.S. hog enterprise production data were obtained from a cross-sectional cost of production study conducted by the Economic Research Service, U.S.D.A. in 1981. Information available for 216 farrow-to-finish swine units in the North Central region and 339 farrow-to-finish swine units in the Southeast region was used to derive the empirical data on annual output and resource use of each swine unit.

Technical efficiency was estimated for each firm using alternative frontier production function approaches. The frontier function approaches used were (1) the "Farrell" linear programming approach to estimating multifactor productivity measures of technical, scale, and input congestion efficiency, and (2) a statistical composed error frontier approach to measuring technical efficiency relative to a random stochastic frontier. The resulting estimates of technical efficiency were used as dependent variables in explanatory regression models which related technical efficiency among firms to specified production characteristics. Production characteristics specified as independent variables were sow herd production intensity, level of confinement, type of management,type of farm business organization, type of manure handling practices, and type of feed and feed processing practices.

Linear programming measures of technical efficiency permitted the derivation of estimates of scale efficiency and congestion efficiency for each hog unit. Mean technical efficiency for hog units in each sample was higher as the frontier function was altered to allow variable returns to scale and weak input disposability in the frontier relationship. Results showed scale and congestion inefficiency to be minor compared to technical inefficiency among swine units in each regional sample. The statistical, stochastic frontier approach gave results showing that technical efficiency was higher for larger size hog units and the estimates of the parameters of the frontier indicated the elasticity of production was less than one for each factor and for all factors collectively.

Results derived from regression models using the deterministic measure of technical efficiency showed very little explanatory power and in many instances the signs, magnitude of the coefficients obtained for explanatory variables were contrary to expectations. Estimates from the regression models using the stochastic frontier indicated a moderate degree of explanation for the variation in technical among firms and estimated coefficients were more plausible.

The existence of technical inefficiency in the hog production process seems quite well documented, but the determinants of hog farm technical efficiency are still unclear based on the results of this study.

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CHAPTER I

INTRODUCTION

The U.S. hog production industry includes a wide range of sizes and systems of production units. Since 1950 the domestic production of hogs (carcass weight) has been fairly constant, in the 12-15 billion pound range. The average size and frequency distribution of hogs farms by size, the timing of production and the type of product has changed markedly in the past 30 years (Van Arsdall, Nelson). Hog enterprises continue to be predominantly farm based, but the tie to the land is no longer essential. Technological advances have contributed to the development of more intensive uses of land and capital resources. Hogs can be produced successfully without pasture using modern systems of total confinement production that are more capital intensive, larger and more industrial in nature.

Background and Setting

The size and frequency distribution of hog producers by size in the U.S. has been shifting. In 1978 the number of producers was about 20% of the number that existed in 1950 (Van Arsdall). The number of farms selling hogs dropped from 2.1 million in 1950 to 450,000 in 1978. Recently hog farms have tended to become larger and more specialized. Producers marketing 1000 animals or more annually accounted for 40% of total U.S. output in 1978 compared with less than 7% in 1950. Large volume producers (marketing 5000 head or more annually) account for an increasing share of total production, currently nearly one sixth of domestic volume and about a 17% annual rate of growth in this size class in recent years (Van Arsdall, Gilliam). Hogs are produced in every state but most output occurs in or near the major feed grain production regions. The corn belt, lake states and northern plains (north central region) accounted for 78% of U.S. production both in 1950 and 1980. The southeast region contributed nearly one sixth of U.S. output in both 1950 and 1978.

Hog sales continue to be an important component of total farm receipts in the U.S., accounting for 15% of the marketings of livestock and livestock products in 1980. Hog production units with 2000 or more hogs are more prevalent in the southeast and southwest than in the north central region. In the south, many of the hog producers are new entrants to commercial production and are larger and more specialized. In the north central area, hogs tend to be produced on diversified farms and utilizing older facilities. Small size hog operations are playing a continually smaller role in the aggregate U.S. production. In the south small and large hog units are more prevalent while intermediate size hog enterprises are predominant in the north central region.

Hog enterprises have been a major contributor of income on farms where they are produced. In 1978 four fifths of all sales of hogs in the major producing regions came from farms where sales of hogs amounted to $10,000 or more and equaled or exceeded 50% of the total sales of all products from the farm (Van Arsdall, Gilliam). The size of the hog operation is related to the size of the farm business. Even the smaller hog operations make important contributions to farm revenue on these farm units.

Hog operations can be classified into three basic systems: (1) Farrow-to-finish, where all phases of production are carried out on the same farm; (2) feeder pig finishing, where pigs are purchased to be fattened for slaughter; and (3) feeder pig production which includes a basic sow unit to produce pigs for sale to feeder pig finishers. Some farmers have a mixture of these systems but most maintain only one of these three types. A large proportion of market hogs are produced on farms with farrow-to-finish systems. In the major hog producing states, of north central and southeast regions, farrow-to-finish enterprises produce four of every five market hogs. Even in the north central and southeastern states where hog production is less concentrated, at least two of every three market hogs came from a farrow-to-finish type of operation (Van Arsdall). In grain deficit regions feeder pig production is likely to account for a larger proportion of total hog sales. For example, in Iowa 18% of total value of sales came from feeder pig sales compared to 38% for Tennessee (Van Arsdall, Gilliam). The predominance of market hog sales from farrow-to-finish enterprises may in part be a reflection of better control of pig health, herd performance, timing of production and marketing alternatives.

Description of the Production Unit

Farrow-to-finish enterprises include all hog production phases prior to marketing. Production techniques used by and available to the producer for each phase vary widely within herd size classifications and production activity, which includes herd health management, housing, feeding and feed handling and waste collection and disposal. Degree of housing varies from production on woodland pasture with little or no shelter to use of specialized confinement buildings for each stage of the life cycle of hogs (Van Arsdall, Nelson). Use of confinement facilities result in greatly increased investment requirement and provide a strong economic incentive for year round production. Methods of managing herd health vary from maintaining a pathogen free environment to standard medicated feed usage. Feed processing and handling techniques range from labor intensive methods of feeding whole grains and supplements by hand to highly mechanized systems of feeding custom formulated complete rations. Similar diversity of methods is observed relative to managing waste collection and disposal.

Hog Production Unit Performance

An examination of a cross-section of hog producers is likely to show considerable variation in the types of production methods and associated production techniques. Variation in levels of confinement and capital use within a sample of hog farms could be expected to have significant impact on unit costs of production, output volume and net returns. Net returns of producers with different types and sizes of hog enterprises can serve as a measure of production performance. This measure, however, is somewhat inadequate as it does not indicate the performance of specific production components. Returns are often calculated on a whole farm basis and not accounted for by enterprise contribution.

Other measures of performance are often used to evaluate the viability of the hog production activity. Many deal with the physical performance of the swine herd. Feed efficiency can be computed using various ratios but productive efficiency is a composite of several production components, not only feeding but also the housing system, herd health programs, and specific production practices. Likewise, a measure, such as days to slaughter, is largely a proxy for the performance of many production activities of the hog enterprise.

Like other farm production activities, to produce hogs several inputs are utilized differing in forms and sources, and can be roughly grouped into the commonly designated land, labor, capital and management categories. Measures of productivity based on average productivity of a specific factor (e.g., production per unit labor) are useful for some purposes of objective comparison. But the sources of efficiency cannot be well understood without consideration of such things as opportunities for factor substitution, the possibility of the existence of size or scale economies or the nature of the factor markets. Productivity measures based on a single factor such as labor, capital or energy use provide limited basis for management recommendations.

Basic budgeting procedures for representing hog enterprises provide point estimates of unit costs of production. Investment and ownership costs evolve from the choice of facilities, while operating costs arise from management practices, performance characteristics of the herd and other variables inputs. Cost of production studies are useful in the evaluation of cost and efficiency and are sometimes referred to as the economic engineering approach. This approach makes use of the notion of a hypothetical firm that is representative of a cross section of firms and serves as a benchmark for measuring operational efficiency. Cost and revenue estimates are then rendered to depict a theoretical or empirical production situation. Unfortunately in the process of generating a representative farm from the observed cross-section, information about the productivity of various production methods and techniques used by farms in the sample cannot be fully delineated without simulating a very large number of representative units.

Theoretical Productions Setting

Cost and efficiency studies of hog production have normally been based on the conventional theory of production. Under some set of technical conditions, production can be expressed as a functional relationship between outputs and inputs. This relationship describes the flows of outputs associated with flows of inputs and so determines the cost structure and expenditure rate for production. Technically efficient enterprises are those production units which produce a unit of output using the least amount of inputs. We might expect that a wide range of factor combinations will yield a given output considering the factor substitution possibilities inherent in the production function. Overall economic efficiency not only requires technical efficiency but also allocative efficiency in equating the marginal value productivity of factors with the relevant factor prices.

Classical marginal analysis addresses only production inputoutput decision in a market setting (allocative efficiency) and assumes a production function that is most efficient from a technical standpoint. Consequently all firms are treated as technically efficient. To apply this conventional theoretical treatment of production to investigate efficient production characteristics is to ignore technical efficiency, an empirically observable dimension of overall economic efficiency. This dimension of inefficiency, failure to achieve technical maximization of output (minimization of input use), has been given relatively limited treatment in the economic literature, but may be a major source of welfare loss in terms of wasted resources. In a pragmatic light, a more thorough understanding of the variation in technical efficiency within a sample of production units offers improved theoretical foundation for production function research and supply analysis using firm level data.

Problem Statement

This study is primarily concerned with the technical productivity of farrow-to-finish swine production units. Hog producers use a variety of production methods and practices to produce a market hog, and as a result considerable variation in cost of production across firms can be expected. Technical inefficiency in input usage related to production methods at the enterprise level is likely to be a component of that observable variation in costs among firms. Technical inefficiency generates costs of production that are higher than those of swine units using "best practice" frontier technology. These higher costs are in proportion to the excessive input usage and are independent of factor prices. This cost component will impact on the viability of the hog farm just as surely as the economic factors of size (or scale) and market prices and costs.

Recognizing that technical inefficiency in the production environment exists and is measurable provides the basis for investigating the productivity of individual components of this environment. Considering the structure of the industry and the changing technology used by hog producers, it is not only important to know what technologies and techniques are available but also their relative productivity. Valuable information may be made available by examining the relationship between technical efficiency and production methods on hog farms in an industry sample of firms.

Objectives

1. To estimate the relative technical efficiency (TE) of individual farrow-to-finish swine units using a cross-sectional

sample. Estimates will be made using the frontier function approach and will be made using two separate function types.

a. Nonparametric frontier production envelope

b. Stochastic frontier production function

2. To specify and estimate an analytical model relating technical efficiency among firms in the sample to specified production characteristics. Coefficients for the independent variables of the analytical model will be estimated using ordinary least squares (OLS) regression procedures.

Summary of Procedures

Input-output data derived from a cross-sectional survey of swine production units will supply the logical production variables used to model the production relationship between market hog output and the factors of production. The production function variables will be used to estimate technical efficiency of the firm by two different frontier function approaches. Each measures firm level technical efficiency as a strictly one-sided deviation from an identified production frontier. The first approach used is a linear programming formulation to measure technical efficiency of a firm as a failure to reach potential output levels given the resources used. The second approach uses regression techniques to estimate a Cobb-Douglas Type production function with a composed error disturbance term. Here the composed error structure is assumed to contain a normally distributed random disturbance term as one source of model error identifying a stochastic production frontier, and a one-sided error disturbance term interpreted as technical inefficiency.

Each frontier function approach will be used to calculate a measure of technical efficiency for each observation in the sample. Each type of technical efficiency measurement will be used as dependent variable of an explanatory explanatory model for testing some hypotheses about the relation between firm level production methods and practices and technical efficiency.

CHAPTER II

LITERATURE REVIEW

Estimating "Frontier" Versus "Average" Production Functions

A basic concept in economics is the production function. It is a systematic way of showing the relationship between amounts of a resource or input and the corresponding output of that product. A production function shows the amount that would be produced by using different amounts of a variable input. In microeconomic production theory the firm's production function is specified as the maximum output allowable from a set of inputs given the technology available to the firm (Henderson & Quardt, 1971).

In order that the understanding be more than purely descriptive, economists have postulated that all economic agents want more of whatever it is they seek. Management wants more output and more net revenue. From the description of the producer's motivation, flow numerous models purporting to explain the production process. All of these models have the economic agent seeking to maximize some function subject to constraint. Most relevant is the firm's manager maximizing net revenue subject to given factor and product prices and his technical production function. A failure in this maximization can be of two classes. One can be a failure in the allocative decision to equate marginal factor prices with marginal value products. If this is true the allocative decision is said to be inefficient. The second type of failure is to what extent does the firm fail to actually produce on the technical production function that yields the maximum output for any given set of inputs. This type of failure is technical inefficiency.

If there are actual differences between firms in technical efficiency, that is, in the manager's ability to achieve the technical maximum, then economic theory dictates that these differences should be measured relative to the technical frontier rather than relative to some "average" firm. "Average" production functions, i.e., those estimated by an Ordinary Least Squares technique that minimizes error on both sides of the estimated function, have received far more attention than frontier functions. The reasons are numerous, the most important being the assumption that firms are on a common technological function, and also the dominance of a statistical theory attuned almost solely to zero average error. Timmer (1971) relates that no formal statistical relationship holds between "average" production function fitted to a functional form and a "frontier" production function enumerated by point sets when it is assumed firm vary in technology. The frontier is drawn from a subset of points that are summarized by the "average" production function. More interesting, if the technology is assumed to vary, is the economic relationship between the two production functions. The economic relevance is the difference between average practices used by firms and the best practices. The frontier represents the best techniques in actual application, and this, of course, is the reason for using the frontier function as a base for judging technical efficiency of other firms. The average production function has a less clear economic interpretation in this respect. As a conceptual construct then, the meaning of average is ambiguous. Average in what sense? Average output? Average size? Average technology?

In a direct sense, technical efficiency is not an economic problem at all, for economics has traditionally assumed that the internal maximizing process in the firm is always completed. Thus, all firms achieve the same amount of output when they use identical amounts of inputs. This is often not so in the real world.

Measuring Efficient Production Frontiers

Estimation of technical efficiency rests on the fundamental relationship between inputs and outputs of the production units. The theoretical definition of a production function is normally in terms of maximum possible output when can be produced from a given quantity of input combinations. The term frontier function can be meaningfully applied to this concept as this function sets limits on the range of possible observations. We may observe firms operating below the frontier, producing less than maximum output, but not above it. The amount by which a firm lies below it can be regarded as a measure of technical inefficiency.

Somewhat outside the mainstream of modern neoclassical production theory, the study of efficiency and its measurement have been undertaken by a number of writers; Farrell (1957), Fare et al. (1978), Aigner et al. (1977), Jandrow et al. (1982). By far the most influential writer on the subject has been M. J. Farrell (1957), who first obtained a partial decomposition of producer economic efficiency into technical and allocative components. Consider a firm using inputs X_i to produce output Y_i and the firm production function is $Y = f(X_1, X_2)$. If it is assumed to be one of constant returns to scale, the frontier technology can be characterized by the efficient unit isoquant exhibiting strong input disposability. As shown in Figure 1, given the frontier isoquant ZZ', technical inefficiency for a given firm is the ratio of input usage at the frontier to amounts of inputs actually used. Let point A be the firm's usage of factors X_1 and X_2. Measured along a ray OA from the origin to the point in question (A), technical efficiency of firm A (TE_A) is the ratio of the distance:OA/OB. Let the line PP' be the ratio of factor prices and tangent to the frontier isoquant ZZ' at point C. Allocative efficiency is measured by the ratio OD/OB since costs at point D is the same as point C but less than the frontier input usage point B.

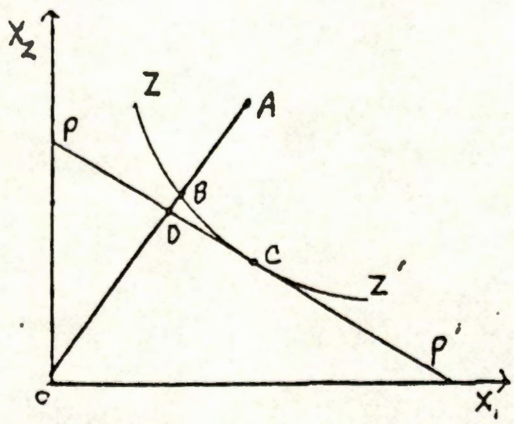

Figure 1. Technical and Pricing Efficiency Using the Frontier Isoquant

There are alternative ways to express the production frontier relationship to be used as the basis of the measure of technical efficiency for a firm. The frontier can be specified as a non-parametric function of inputs that is essentially an envelope closure of observed input-output coordinates. This is the method used by Farrell (1957), Fare et al. (1983). It can be estimated using linear programming procedures.

Farrell confined his attention to production technologies assumed to have constant returns to scale and frontier isoquants exhibiting only stage II of production. In more recent development concerning the measurement of producer efficiency, Fare, Grosskopf and Lovell (1985) generalize and augment the Farrell assumptions to allow the decomposition of technical efficiency into their structural components, technical, scale and congestion efficiency. Scale and congestion inefficiency are defined in the case where the frontier production technology is shown to deviate from constant returns to scale and the strong input disposability conditions.

The production frontier is called deterministic if all observations must lie on or below the frontier. For the deterministic frontier approach the tools of statistical inference do not apply and no statistical properties of estimators results.

The frontier can also be specified as an explicit stochastic composed error model of the input-output relationship and estimated with maximum likelihood techniques as did Aigner et al. (1978), Jandrow et al. (1983). Stochastic frontier estimation as the basis of measuring TE by means of composed error (ML-CE) modeling start from a much different philosophy with regard to the phenomenon of technical inefficiency. In general, by attributing some part of the variation among firms, relative to the production frontier, to be random phenomena or disturbances because of omitted variables or measurement error, one arrives at estimating potential full production capacity output of the frontier technologies. Observed inefficiency relative to this type of stochastic frontier is assumed to be related then to capacity utilization (idle resources) and inefficiency in the production process. The only common characteristic between these approaches is that the one-sided deviation from the frontier is interpreted as technical inefficiency. Whether the frontier is characterized as deterministic or stochastic, it is accepted that the one-sided deviation from the frontier embodies the firm's inefficiency in technical productivity.

Measuring Technical Efficiency Relative to a Deterministic Nonparametric Frontier

The shortcomings of the Farrell Approach to measuring efficiency in complex technologies has led to several developments. Fare et al. (1983) have augmented the Farrell measure of technical efficiency by the addition of a separate measure of structural efficiency: congestation. A producer is technically efficient if production occurs on the boundary of the producer's production possibility set. A technically efficient producer is said to be structurally efficient if production occurs in the uncongested or "economic" stage 2 of the boundary of the production possibility set, and structurally inefficient if production occurs in a congested, "uneconomic," region of the boundary. Structural inefficiency can only occur if some subset of inputs are not freely disposable. Congestion exists if production occurs in that backward bending region of the frontier. The concepts of technical and structural inefficiency are independent of factor prices and traditional producer goals.

Even if a producer is efficient in a private sense and succeeds in solving the above optimization criteria, the resulting production may still be suboptimal in a social context. There may exist some divergence between actual firm size and ideal size consistent with long-run competitive equilibrium conditions. Fare et al. (1983) define a component of firm efficiency called scale efficiency. A firm is said to be scale efficient if the technology exhibits constant returns to scale. A firm may be scale inefficient if the technology exhibits nonconstant returns to scale. An index of scale efficiency based on technically optimal size was proposed by Forsund and Hjalmorsson (1974) and has been implemented by Banker, Charnes and Cooper (1983) and Fare et al. (1983). Fare showed how to determine whether scale inefficiency is due to increasing or decreasing returns to scale (Fare et al., 1985).

Scale inefficiency results when the frontier reference for a firm exhibits technological deviation from constant returns to scale technology. Inefficiency referred to as congestion occurs when a firm could dispose of some inputs and generate an increase in output relative to technologies structured to allow this input adjustment. A measure of pure technical efficiency of the firm is considered to be separate from scale or structural sources of technical inefficiency.

Rather than using OLS procedure to fit a parametric function to the data, mathematical programming procedure is used to bound or envelope the data with a nonparametric production frontier. This permits the computation of the productive efficiency of individual firms in the sample by comparing their total factor productivity to the best practice frontier total factor productivity in the sample. It is possible to identify efficient and inefficient firms on this basis and decompose measured efficiency for each firm into purely technical, scale and congestion components. This approach has the advantage of providing a nonparametric representation of efficient technology, the structure of which is determined by weak regularity conditions and by the data rather than the choice of parametric form (Fare et al., 1983). The disadvantage of this approach is that since the results are deterministic and each case is given equal consideration in outlining the frontier the measures are sensitive to outlier observations that are the result of both error in measurement and random influences. This approach to measuring TE requires considerable confidence in the quality of data; explicitly the assumption is made that errors are negligible and that random disturbances do not exist.

The performance measure used to evaluate the technical productivity of firms in a sample is total factor productivity or output per unit of input and are extensions of the original Farrell concept. The restrictive technological assumption held by Farrell, of constant returns to scale and strong input disposability, are relaxed to allow derivation of scale and congestion efficiency. Each of these performance measures are solutions to linear programming problems.

Computation of Technical Efficiency Relative to a Nonparametric Frontier

Assume there are k firms, each producing a single output Y, using n inputs $x = (X_1, X_2, \ldots X_n)$. Label the vector of observed output as M where M is of the order (K,1). Label the n vectors of observed inputs by N, where N is of the order (K,n). Further assume that each output is producible; that each input is required by at least one firm and that each firm uses at least one input. Next let $Z = (Z_1, Z_2, \ldots Z_K)$ be the firm intensity level of each of the K firms. These K firms which use n inputs to produce one output are useful in modeling the reference technology relative to which efficiency is measured. Following the convention used by Fare (1983), several different piecewise linear reference technologies are used to evaluate technical, structural and scale efficiencies. These reference technologies vary in the restrictions placed on the technology with respect to disposability of inputs (weak or strong) and the scale properties of the technology (constant, decreasing or increasing). The strategy is to construct a series of nonparametric frontier technologies of increasing generality each of which bounds or envelops the data. The relationships among the four calculated measures of efficiency, $K(y,x)$, $W^*(y,x)$, $W(y,x)$, and $F(y,x)$, enable us to establish the derived measures of scale and congestion efficiency S(y,x) and C(y,x) for each observation.

The data are initially enveloped with a restrictive technology exhibiting constant returns to scale (CRS) and strong disposability of inputs (SDI). The measure of technical efficiency relative to this technology, denoted [K(y,x)] is calculated by solving the programming problem:

$$(1) \qquad K(y,x) = \min.\ \theta$$

$$\text{S.T.} \quad 1)\ ZM \geq y°/\theta$$

$$2)\ ZN \leq X°$$

$$3)\ Z \in R^k_t$$

where y° and x° are the observed output and observed input usage of the firm whose efficiency is being measured in each L.P. problem. To illustrate, consider Figure 2. Three observed firms labeled A, B, C are plotted in input-output space.

The CRS-SDI technology that bound the data and which is described in (1) is the area bounded by the ray OD and the x-axis. Only observation B is overall technically efficient relative to this technology. A and C are too small and too large, respectively, to be overall technically efficient.

Next the data are enveloped by a still less restrictive technology, one that exhibits nonincreasing returns to scale, (NIRS) and SDI. The measure of technical efficiency relative to this less restrictive technology is calculated by solving the programming problem:

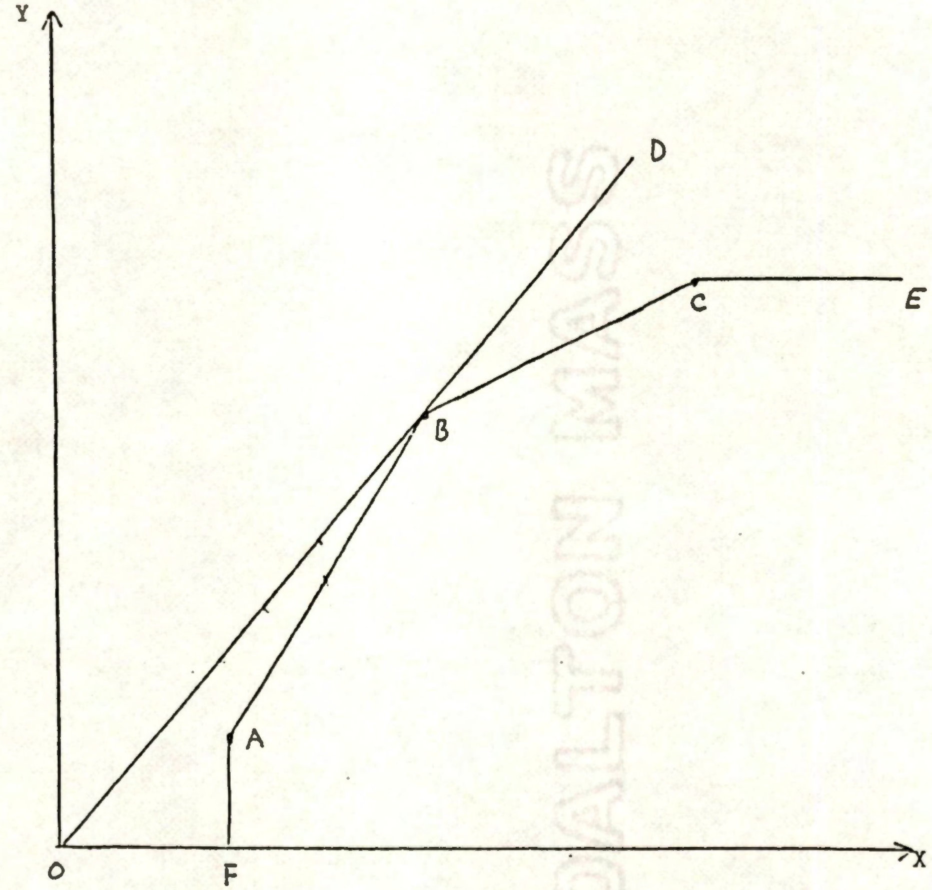

Figure 2. Example of the Changes in the Shape of the Production Frontier as the Scale Properties of the Frontier Become Less Restrictive.

$$(2) \qquad W^*(y,x) = \min.\ \theta$$

$$\text{S.T.} \quad 1) \quad ZM \geq y^\circ/\theta$$

$$2) \quad ZN \leq x^\circ$$

$$3) \quad Z \in R_t^k, \quad \sum_{i=1}^{k} Z_i \leq 1$$

Referring to Figure 2, the NIRS-SDI technology that bounds the data and which is described by the constraints in (2) is bounded by

OBCE and the x-axis. This technology envelopes the data more closely and now both observations B and C are overall technically efficient. Observation A is too small to be technically efficient relative to this NIRS-SDI technology.

Next, in following the outlined strategy we envelop the data with a still less restrictive technology, one satisfying variable returns to scale (VRS) and SDI. This measure of technical efficiency relative to this technology is calculated by solving the programming problem:

$$(3) \qquad W(y,x) = \min.\ \theta$$

$$\text{S.T.} \quad 1)\ ZM \geq y^{\circ}/\theta$$

$$2)\ ZN \leq X^{\circ}$$

$$3)\ Z \in R_t^k,\ \sum_{i=1}^{k} Z_i = 1$$

In Figure 2, the VRS-SDI technology that bounds the data and which is described by the constraints of problem (3) is bounded by FABCE and the x-axis. All three observations, A, B and C, are technically efficient relative to this VRS-SDI technology.

Armed with these three different measures of technical efficiency, $K(y,x)$, $W^*(y,x)$ and $W(y,x)$, we can now derive a measure of scale efficiency which measures lost output due to deviation from CRS; the technically optimal scale. The measure of scale efficiency is given by the ratio:

$$S(y,x) = K(y,x)/W(y,x).$$

From the above modeling of the piecewise linear reference frontiers we not only can evaluate if scale inefficiency exists at (y,x) but also the nature of the scale inefficiency by comparing the efficiency measures from the three different problems.

1. $S(y,x) = 1 \Leftrightarrow K(y,x) = W(y,x) \Leftrightarrow$ CRS (constant returns to scale) exists at (y,x).

2. if $S(y,x) < 1$, and $K(y,x) = W^*(y,x)$ then IRS (increassing returns to scale) exists at (y,x).

3. if $S(y,x) < 1$ and $K(y,x) < W^*(y,x)$ then DRS (decreasing returns to scale) exists at (y,x).

Finally, the data are enveloped with the least restrictive technology, one satisfying VRS and weak disposability of inputs (WDI). The measure of technical efficiency relative to this technology is calculated by solving the programming problem.

$$F(y,x) = \min. \theta \tag{4}$$

$$\begin{aligned} \text{S.T.}\quad & 1)\ ZM \geq y^\circ/\theta \\ & 2)\ ZN(1/\sigma) = X^\circ \\ & 3)\ 0 < \sigma < 1 \\ & 4)\ Z \in R^k_t,\ \sum_{i=1}^{k} Z_i = 1 \end{aligned}$$

The distinction between F(y,x) and W(y,x) can be seen by examining Figure 3.

F(y,x) is the reference technology exhibiting VRS and WDI while W(y,x) exhibits VRS and SDI. If technology satisfies only WDI then observation A is technically efficient, $(F(y,x) = 1)$ since X_A is incapable of producing $y > Y_A$. However, if technology satisfies SDI then observation A is technically inefficient, ($W(y,x) < 1$), because by reducing the use of X_2, input bundle X_B could be used to produce a larger output $Y_B = Y_A/W(Y_A,X_A)$. Now a measure of congestion can be

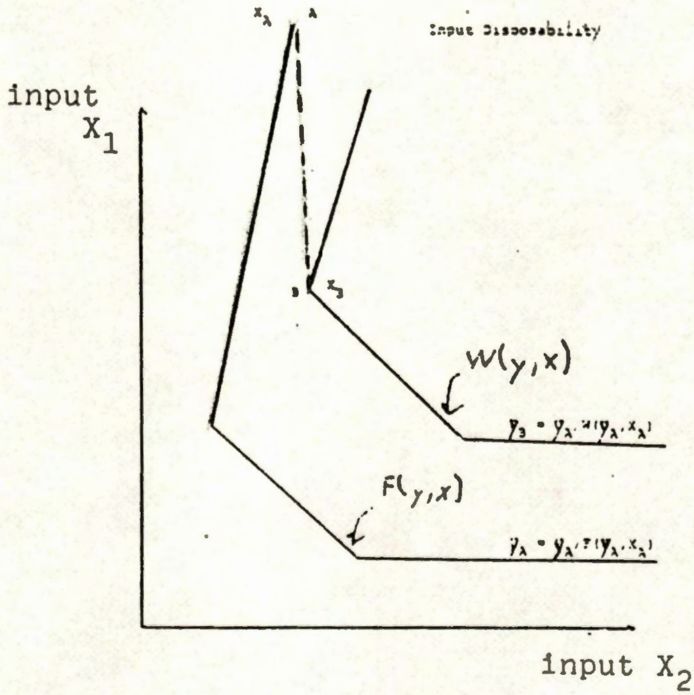

Figure 3. Comparison of Weak and Strong Disposability Leading to Measurement of Congestion Inefficiency.

derived which measures the lost output due to lack of strong disposability of inputs. The measure of congestion $C(y,x)$ is given by:

$$C(y,x) = W(y,x)/F(y,x)$$

and is the ratio of two efficiency measures modeling assumed firm technologies exhibiting strong and then weak input disposability.

By using this method of modeling the firm's production environment we can obtain the following efficiency measures for each observation (see Table 1).

Table 1. Computed Technical Efficiency Measures Using Linear Programming Approach

TE Measure	Type of Reference Technology
1. $K(y,x)$	CRS - SDI
2. $W^*(y,x)$	NIRS - SDI
3. $W(y,x)$	VRS - SDI
4. $F(y,x)$	VRS - WDI

From these calculated measures we derive the measures of scale and congestion efficiency:

5. $S(y,x) = \dfrac{K(y,x)}{W(y,x)} \leq 1$

6. $C(y,x) = \dfrac{W(y,x)}{F(y,x)} \leq 1$

The original Farrell measure of technical efficiency, K(y,x) is deconposable using the methods of Fare (1983), into its component parts:

$$K(y,x) = S(y,x) \cdot C(y,x) \cdot F(y,x).$$

Measuring Technical Efficiency Relative to a Stochastic Frontier Production Function

Traditionally economists have dealt with the technology of production either theoretically by assuming a production function which expresses the maximum output obtainable from a given bundle of inputs or empirically using the notion of the average production function with fixed technology. The work of Farrell (1957) represents the first major attempt to estimate frontier production functions. Following Farrell, the majority of the work has used mathematical programming techniques to model the frontier technology.

More recent work has been directed at the estimation of a stochastic production frontier and measuring firm technical efficiency relative to the stochastic frontier. This approach involves the specification of a parametric frontier production function with an error term made up of two components, one normal and the other a one-sided distribution (Aigner et al., 1977). This convention is born in the argument that to lump exogenous shocks (good and bad luck) with the effects of measurement error and inefficiency into a single one-sided term and to label the mixture inefficiency is questionable (Forsund et al., 1980).

Earlier work on the estimation of parametric frontier production functions is characterized by the work of Chu (1968), Afriat (1972) and Richmond (1974) who assumed a function giving maximum possible output as a function of certain inputs; $Y_i = f(X_i;\beta)$ where Y_i is output, X_i is a nonstochastic input vector and β is an unknown parameter. Aigner and

Chu (1968) and Timmer (1971) used mathematical programming to estimate the parameters of the model based on a crosssection of firms. Their technique minimized the linear sum of an implied one-sided error term. Again this technique of estimation and the assumption concerning the phenomenon of technical inefficiency are problematic to drawing inferences from results since the estimates have no statistical foundation.

Schmidt (1976) felt it preferable to incorporate the possibility of measurement error and of other unobservable shocks in a less arbitrary fashion. He explicitly added a one-sided disturbance term to $Y_i = f(X_i;\beta)$, which yields the model: $Y_i = f(X_i;\beta) + E_i$, $i = 1,\ldots,n$ where $E_i < 0$. Given a distributional assumption for the disturbance term, the model can be estimated by maximum likelihood techniques. With respect to this modeling of frontier technology, there are also some valid criticism concerning the composition of the error structure since it is assumed to contain only observed inefficiency relative to the frontier and makes no representation for normal random output variation due to other types of disturbances.

A more direct approach is to specifically model the error process implied by the concept of a stochastic production frontier. Aigner et al. (1977) proposed using the model, $Y = f(X_i;\beta) + E_i$, $E_i = V_i + U_i$, $i = 1,\ldots,n$. The error component V_i represents the symmetric disturbance: the (V_i) are assumed to be independent and identically distributed as $N(0,\sigma^2)$. The error components U_i are assumed to be distributed independently of V_i and to satisfy $U_i < 0$. Some kind of distributional assumption must be made for the one-sided component U_i.

Aigneer et al. (1977) considered both a normal distribution truncated at zero, and an exponential distribution. The nonpositive disturbance U_i reflects the fact that the output of each firm must lie on or below its stochastic frontier, $[f(X_i;\beta) + V_i]$. Any deviation is the result of factors under the control of the firm, such as technical inefficiency relative to labor, capital or other inputs. The frontier itself can vary randomly across firms. With this interpretation the frontier is clearly stochastic as the random disturbance

$$V_i \lesseqgtr 0$$

is the result of favorable and unfavorable events, and errors of observation and in measurement. Of particular interest and central to this proposed study, the by-product of this approach is that we can estimate the relative size of the variances of V_i and U_i and that in principle, productive efficiency can be measured by the ratio of actual (Y_i) to frontier output; $Y_i/[f(X_i;\beta) + V_i]$. If information about the firm's productive inefficiency of the firm is to be used to investigate the manageable sources of inefficient production, the measure should not contain "inefficiency" from sources that are beyond the control of the firm.

Consider a simple linear production function model such as Y = XB + E, where E = V + U. Assume that the distribution of the error components are $V \; N(0,\sigma_v^2)$ and $U \; |N(0,\sigma_v^2)|$. A distribution function of the sum of these component distributions has been derived and used to specify the relevant density function E (Aigner et al., 1977),

$$f(\varepsilon) = \frac{2}{\sigma} f^* \frac{\varepsilon}{\sigma} \quad [1 - F^*(\varepsilon\ \sigma^{-1})], \ - \infty < \varepsilon < + \infty.$$

In the above density function, $\sigma^2 = \sigma_v^2 + \sigma_u^2$, $\lambda = \sigma_U/\sigma_V$ and $F^*(.)$ are the standard normal density and distribution functions, respectively. The term λ can be interpreted as an indicator of the relative variability of the two sources of error.

Assuming we have a random sample of N observations, the relevant log-likelihood function as presented by Aigner et al. (1977) is:

$$\text{(6)} \qquad n \quad (y|\beta,\lambda,\sigma^2) = N\ n \frac{\sqrt{2}}{\sqrt{\pi}} + N\ n\sigma^{-1}$$

$$+ \Sigma \quad n[1-F^*(\varepsilon_i \lambda \sigma^{-1})] - \frac{1}{2\sigma^2} \sum_{i=1}^{N} \varepsilon_i^2,$$

The subscript i indexes the observations. Various solution algorithms are available for finding the optimum values of β, λ, and σ^2 using maximum likelihood estimation techniques.

When a model of this form is estimated, one readily obtains residuals, $\hat{\varepsilon}_i = Y_i - g(X_i;\beta)$ which are estimates of the error term ε_i. Further, the problem of decomposing these estimates into separate estimates of the components V_i and U_i no longer remains a barrier to evaluating firm technical efficiency. The average technical efficiency as the mean of the distribution of the U_i term can be calculated (Aigner et al., 1977). It is also clearly desirable to be able to estimate the technical inefficiency (U_i) for each observation.

The above desirable state should be possible because $\varepsilon_i = V_i + U_i$ can be estimated and it contains information on U_i. J. Jandrow et al.

(1982) proposed a method for estimating the technical efficiency for each observation. They proceeded by considering the conditional distribution of U_i given E_i. Either the mean or the mode of this conditional distribution can be used as a point estimate of U_i. Jandrow et al. (1982), considered both a half normal and an exponential distribution of U_i and showed how to evaluate these expressions.

In the half normal case, the two part distribution E_i contains the disturbances $V_i \sim N(0,\sigma_v^2)$ and $U_i \sim |N(0,\sigma_u^2)|$, and define $\sigma^2 = \sigma_v^2 + \sigma_u^2$, $\sigma_* = -\sigma_u^2\ \varepsilon/\sigma^2$ and $\sigma_*^2 = \sigma_u^2\ \sigma_v^2/\sigma^2$. Jandrow (1982) offers a theorem which states that the conditional distribution of U_i given ε_i is that of a $N(\mu_*,\sigma_*^2)$ variable truncated at zero. This conditional distribution is used to draw inferences about U_i and confidence intervals for the point estimates of U_i can be constructed. The mean is,

$$E(u|\varepsilon) = \mu_* + \sigma_* \frac{F(-\mu_*/\sigma_*)}{1-F(-\mu_*/\sigma_*)}$$

where f(.) and F(.) are the standard normal density and distribution functions, respectively. Jandrow et al., note that $-\mu_*/\sigma_* = \varepsilon N\sigma$ where $\lambda = \sigma u/\sigma v$ is the same point at which f and F are evaluated in calculating the likelihood function. Thus the point estimate of the mean of U is given by:

$$E(u|\varepsilon) = \sigma_* \left[\frac{f(\varepsilon\lambda/\sigma)}{1-F(\varepsilon\lambda/\sigma)} - \frac{\varepsilon\lambda}{\sigma}\right]$$

In the above representation, the true value of μ_* and σ_* are unknown.

Thus in using the above result, the term μ_* and σ_* must be replaced by their estimates $\hat{\mu}_*$ and $\hat{\sigma}_*$. In place of E(U/E) we must use $\hat{E}$(U/E).

Using the Estimates of Technical Efficiency

The measurement of technical efficiency (TE) as addressed in the first objective provides a basis for comparison of observations. To simply summarize the relative magnitude of technical inefficiency observed in a sample of farms is a somewhat shallow comparison. If measured without error technical efficiency is an indicator of relative performance ofT achieving the producer goal of maximizing production with a given set of productive resources. A more meaningful use of the estimates of technical efficiency at the firm level would be to relate this information to firm observation characteristics. A number of economists interested in the measurement of technical efficiency have done just that (Timmer, 1971; Farrell & Fieldhouse, 1962; Wildermuth & Carter, 1967; Seitz, 1971; Merller, 1976; and Byines et al., 1983) .

In previous work authors have recognized that a better understanding of the existence and measurement of firm technical efficiency is necessary to form a more complete description of the performance of an economic unit or its behavior in the market. Without appropriate measures of technical efficiency, efforts to estimate cost curves, provide only limited usefulness for production planning. Because technical inefficiency affects substitution rates between resources, the derived optimal resource combination may not render minimum cost. This limits the usefulness of cost functions for managers making size decisions (Kadlek & House, 1962). The study of technical efficiency has found application in agriculture industries and manufacturing. In measuring TE some studies report results that are interpretable at the firm level while others are interpretable at a more aggregate state or industry level. A 1971 article by Seitz reports measured technical efficiency of individual steam-electric generating plants. Further, he carried the analysis to investigate the relation between efficiency and location and construction of the generating plant. Wildermuth and Carter (1962) measured technical efficiency of California tomato producers in a before and after situation. They used this information to study the growth and adjustment process of producers in a rapidly changing environment. Here again the analysis included forming hypotheses useful for specifying and exploratory model that relates technical efficiency to adjustment performance of the farm. More recent examples include the Brynes et al. (1985) study of the productivity differences (technical efficiency) between surface coal mines as related to the incidence of unionized labor in the sample of mines. In Timmer (1971), technical efficincy was measured for each state. Here state level agriculture statistics for farm income and resource use were used to generate an "average farm" for each state as the individual observations. Following this, Timmer reported on attempts to explain technical efficiencies in terms of potential socioeconomic factors such as days worked off the farm, proportion of tenant farm operators in the states, age of farmers, and education of farmers.

The above references cited serve to indicate a research interest by economists in not only measuring technical inefficiency, but also in the discovery of potential determinants of such and how this information can improve ones understanding of economic theory and its applications.

CHAPTER III

PROCEDURES

Source and Description of Data

The data supporting this study was obtained entirely from a 1981 survey of hog producers conducted by USDA's Statistical Reporting Service (SRS) in cooperation with the Economic Research Service (ERS). The collected survey information included not only the characteristics of the farms producing hogs but also the type of equipment, facilities and production practices used. Information used in this study applies to the year 1980. The 1981 survey was designed primarily to provide information about the changing structure of the swine industry and the nature of production practices used on various types of hog farms.

The 1981 survey included information from 1264 farms with total sales of 2.9 million hogs and pigs in 1980. Farms surveyed were located in 18 states where over 90% of all U.S. hogs and pigs are produced. The states were divided into two regions having differing agricultural characteristics; 11 states in the North Central region, and seven states in the southeast (Figure 4). Farms were classified by type of hog enterprise operated in 1980. The survey sample was selected randomly from a population stratified by size of hog enterprise. Sample weighting schemes were used to ensure that enterprise types and sizes the sample were required to be one of the three basic types: feeder pig, farrow-to-finish, a feeder pig finisher. Sales had to be at least 100 head of hogs or pigs during

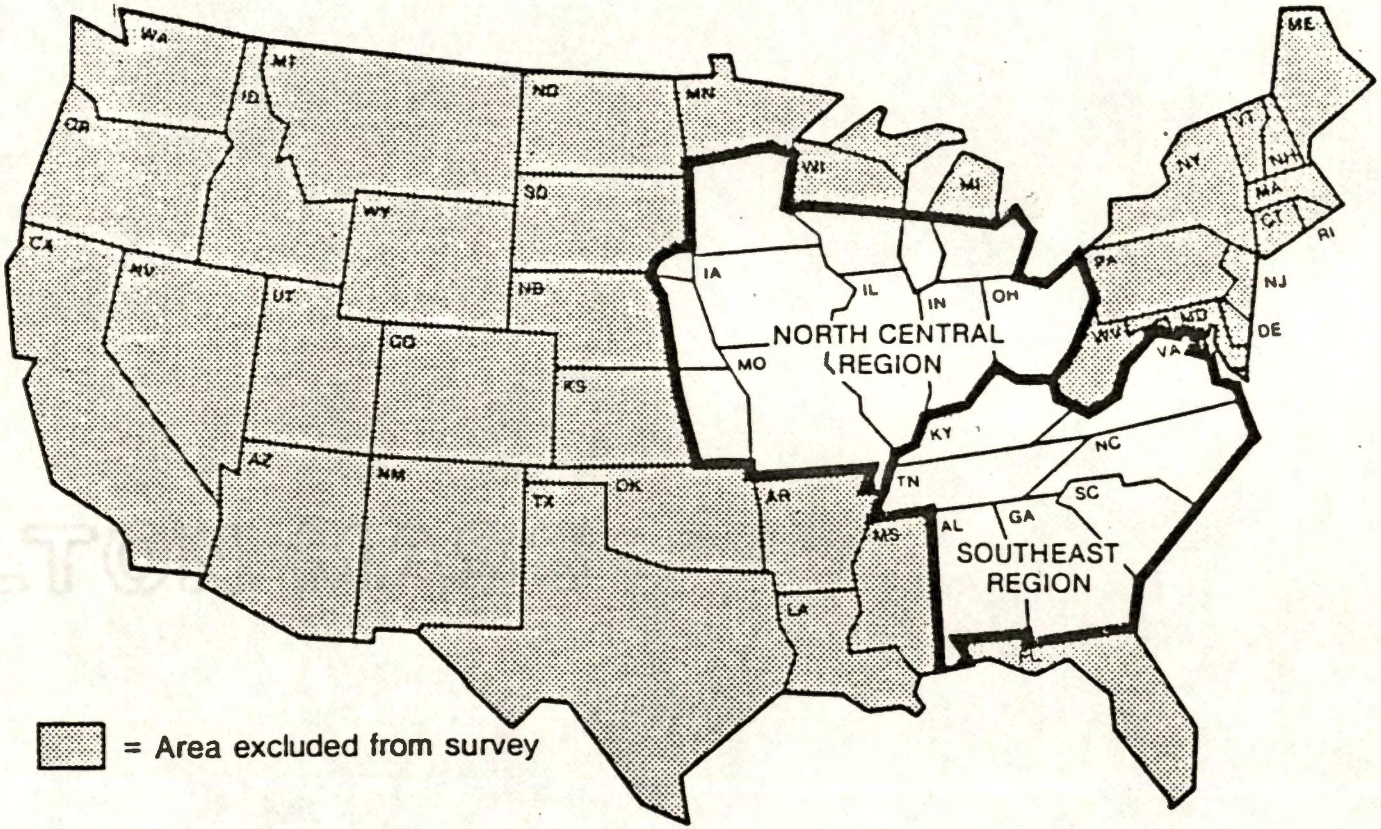

Figure 4. Location of U.S. hog production regions used in the study.

1980 with at least 75% coming from one of the three types of enterprise.

To establish the survey sample, the population of hog farms qualifying for the sample was divided into six classes based on the number of hogs and pigs sold annually. The size classes were: 100-199; 200-499; 500-999; 1,000-1,999; 2,000-4,999; and 5,000 or more. The population of each size type was sampled randomly to obtain adequate observations for each situation (Van Arsdall and Gilliam).

Only the sample of hog production units classified as farrow-to-finish were used in this study. This subdivision was only a portion of the survey sample, but the random nature of the stratified sample of farrow-to-finish producers was likely intact. This study was primarily concerned with the efficient production of a market hog from hog enterprises that engage in all phases of the production process. The above size classification was preserved for expository purposes only, facilitating discussion of data and results as related to firm size.

Selection of Variables

Hog production, like any production process, can be represented by a functional relationship based on the productivity of factors. The production function describes the way that resources are transformed into outputs over time. Production functions are altogether expressions of a technical relationship and are necessary to derive economic relationships of minimum cost and maximum profit. Specific types of production function will be introduced later, but for the present purpose it is only necessary to select the relevant inputs of the production function.

Selection of the input variables follows logically from the hog production process and the underlying theory of production. The production model used included the following variables:

1. Output: Y; hundredweight of hogs marketed annually.
2. Input categories:

   X_1; Total hour of labor (annual) used in the hog enterprise.

   X_2; Average pounds of all feed used per cwt. of hog produced, times annual output.

   X_3; Capital ($flow) for machinery, equipment and facilities assets.

   X_4; Expenditures ($) for (a) vet and medicine, (b) custom services, (c) electricity and heating fuels.

Measurement of Input Variables

Labor: The labor input included only labor used for the hog enterprise activities. It was the sum of:

1. annual operator hours of labor input
2. annual unpaid labor hours
3. annual total hours of hired labor

   X_1 = annual amount of labor input used directly for hog enterprise.

Feed: The feed variable was defined as the total annual feed used for the hog enterprise including feed for maintenance of sow herd.

This measure of feed input was the product of the average amount of <u>all feed</u> used per hundred pounds of hog produced and the annual output volume in hundredweight of hogs.

$$X_2 = \text{(avg. lbs. of feed/cwt. x annual cwt. produced).}$$

<u>Capital</u>: This input was designed to capture the flow of capital expenditure for the enterprise and was derived from knowledge of the specific capital items used by each producer for the hog operation. When machinery and/or equipment were used jointly for producing other farm products, this variable included only that proportion of the capital flow used by the hog enterprise.

$$X_3 = \text{capital (\$) flow related to stock of capital assets;}$$

It included annual charges for investment in buildings, machinery and equipment used for hogs and was the sum of:

1. Depreciation
2. Insurance
3. Taxes
4. Interest
5. Maintenance and repairs
6. Fuel and lubricants (machinery)

Land inputs in this model are not considered as a separate factor of production. Annual operating expenses associated with land as (pasture lot) inputs to the enterprise are included in the capital flow variable of the model. Ownership cost of land inputs are excluded from the specified production relationship. Land input as a factor in the production of hogs was included when applicable because of the supplemental feed, in the form of forage, that is available to the hogs, and also because of the health aspects of the pasture providing a sanitary disease free environment. The capital flow variable included operating expenses of annual pasture lot maintenance activities such as pasture renovation and fence upkeep.

Miscellaneous expenditure: This input was a measure of the dollar value of annual expenditures for some other inputs used for hog production services. It included

1. Vet and medical supplies
2. Custom services
3. Electricity and heating fuels

X_4 = dollar value of miscellaneous annual expenditures

Thus, the generalized production relationship was assumed to be as follows:

$$\text{cwt. of hogs} = f(\underset{(X_1)}{\text{Labor}}, \underset{(X_2)}{\text{Feed}}, \underset{(X_3)}{\text{Capital}}, \underset{(X_4)}{\text{Misc. Exp.}})$$

This production function specification was assumed to be a complete logical model that described the flow of market hog output from the enterprise as related to the flow of labor, feed, capital and miscellaneous variable inputs.

Observed Production Data

Descriptive statistics of the input-output data on hog enterprises by region are presented in Tables 2 and 3. The mean and standard deviation of the mean for each variable are shown as well as the ratio Y/X which relates the average number units of output (Y) observed per units of observed average input usage (X). The size category stratification, C1 to C6, was included to provide more detail about the sample farms. Each regional sample was obtained by subsetting a stratified random sample of hog units, and neither sample can be considered representative of the population of farrow-to-finish hog production units. The cross sectional samples include only farrow-to-finish producers responding to the 1981 U.S.D.A. Cost of Production of Hog Survey. The U.S.D.A. sample included hog producers of all three types. The size and number distribution of farrow-to-finish hog farms is shown in Tables 2 and 3. Following exclusions for incomplete data, the north central sample included 216 observations and the southeast sample included 339 observations. It should be noted that while the north central region was the larger geographic area and also contributed the larger volume to the domestic production of hogs, the southeast region was the larger sample of hog farms with complete information on key input variables such as feed and labor. This result may be a reflection of the more diversified character of the farms in the north central region where monitoring and recording input allocations was more difficult. It should also be noted that the upper end of the size distribution was open-ended,

Table 2. Means, standard deviations, and output to input ratios for the North Central Region input-output variables.

Output Categories	Stats	Live cwt. produced/yr.	Labor hrs./yr.	Feed cwt./yr.	Capital $	Misc. Expenditures $
	$\bar{X}$	4,974.27	3,731.09	19,951.35	42,569.68	11,715.77
ALL	Std. Dev.	6,523.30	4,490.69	28,176.14	51,855.64	19,228.11
N = 216						
C1[a]	$\bar{X}$	350.50	802.05	1,494.17	5,227.43	720.55
N = 20	Std. Dev.	66.99	430.44	435.47	2,622.75	475.57
	Y/X	.44.23	.07	.49		
C2	$\bar{X}$	826.04	1,125.08	3,369.41	11,140.38	1,487.47
N = 40	Std. Dev.	238.09	685.75	1,132.50	6,311.13	1,013.48
	Y/X	.73	.24	.07	.56	
C3	$\bar{X}$	1,749.69	2,028.38	7,378.58	20,845.28	3,760.61
N = 42	Std. Dev.	312.38	962.67	2,234.31	9,747.24	2,418.50
	Y/X	.86	.24	.08	.46	
C4	$\bar{X}$	3,443.24	3,140.06	14,107.19	34,031.64	6,980.35
N = 48	Std. Dev.	682.19	1,588.67	4,289.10	12,613.98	4,367.30
	Y/X	.91	.24	.10	.49	
C5	$\bar{X}$	7,529.32	5,123.08	28,599.14	69,495.70	18,735.68
N = 45	Std. Dev.	2,143.58	2,809.88	8,585.52	34,072.45	13,827.98
	Y/X	1.49	.26	.11	.40	
C6	$\bar{X}$	21,764.37	13,254.61	89,122.90	143,268.90	53,395.43
N = 21	Std. Dev.	7,202.25	7,863.21	42,637.43	94,262.78	32,283.65
	Y/X	1.64	.24	.15	.40	

[a]C1 = 100-199 head; C2 = 200-499 head; C3 = 500-999 head; C4 = 1000-1999 head; C5 = 2000-4999 head; C6 = > 5000 head.

Table 3. Means, standard deviations, and output to input ratios for the Southeast region input-output variables.

Output Categories	Stats	Live cwt. produced/yr.	Labor hrs./yr.	Feed cwt./yr.	Capital $	Fuel (elec., oils) Vet. Serv. Custom Serv.
	$\bar{X}$	4,574.71	4,696.61	18,658.85	34,767.54	11,715.77
ALL	Std. Dev.	6,523.30	4,490.69	28,176.14	51,855.64	19,228.11
N = 339						
C1[a]	$\bar{X}$	384.92	803.29	1,539.53	4,933.85	723.52
N = 36	Std. Dev.	62.09	391.84	622.12	3,765.61	796.04
	Y/X	.43.23	.07	.48		
C2	$\bar{X}$	795.40	1,641.25	3,335.95	11,639.75	1,986.84
N = 68	Std. Dev.	214.37	1,268.68	1,126.47	10,256.97	3,157.88
	Y/X	.48	.24	.06	.40	
C3	$\bar{X}$	1,714.24	2,555.55	6,970.31	18,408.15	2,924.52
N = 70	Std. Dev.	341.58	1,550.57	2,065.64	11,494.94	2,121.09
	Y/X	.67	.24	.09	.58	
C4	$\bar{X}$	3,384.24	4,304.15	13,603.24	31,576.36	7,779.36
N = 72	Std. Dev.	692.29	2,244.85	4,070.50	16,935.17	5,135.99
	Y/X	.79	.24	.10	.43	
C5	$\bar{X}$	7,544.03	7,381.42	29,925.99	60,419.92	19,937.24
N = 66	Std. Dev.	2,124.82	3,599.50	9,285.19	31,358.04	13,209.50
	Y/X	1.02	.25	.12	.37	
C6	$\bar{X}$	23,067.93	17,614.52	96,355.66	121,120.48	57,799.67
N = 27	Std. Dev.	9,817.61	9,009.83	48,801.74	55,415.67	85,065.65
	Y/X	1.31	.24	.19	.40	

[a]C1 = 100-199 head; C2 = 200-499 head; C3 = 500-999 head; C4 = 1000-1999 head; C5 = 2000-4999 head; C6 = > 5000 head.

allowing observations in size category C6 to show extreme production ratios and possibly having a disproportionate influence on overall mean and standard deviation values for the sample. The frequency of observations by size was primarily the result of a sampling design but was also the result of eliminating from the sample those farrow-to-finish producers who gave no response to specific survey questions about feed and/or labor inputs. Eliminated sample units may not have been randomly distributed.

Mean annual output for the 216 hog producers in the north central region was approximately 5000 hundredweight of live market animals (2100 head). The producers in the sample utilized an average of 3731 hours of labor which is approximately 2 full-time workers, and 20,000 hundredweight of complete feed, about 955 pounds per head (Table 2).

Output to input ratios, (Y/X) for the north central sample are shown in Table 2. For the input variables labor and capital, this ratio, Y/X, reflected increasing average productivity with increase in output category. Labor productivity increased 4 fold across the output categories from .44 units of output per unit of labor for size category C1 to 1.64 units of output per unit of labor for category C6. For the capital input, the ratio Y/X increased over 2 fold from .06 units of output per unit of input for C1 to .15 units of output per unit of input for output category C6. For the feed and miscellaneous expenditures, productivity changes across size categories were small and were not as obvious.

Descriptive statistics for the production variables for the southeast sample are presented in Table 3. For this cross-sectional sample of 339 observations, mean annual output was 4574 hundredweight of live market animals (1900 head). The mean annual labor input was 4691 hours, well over 2 full-time workers. The mean level of feed use was 18,658 hundredweight of complete feeds or approximately 982 pounds of feed per head marketed. Output-input ratios, Y/X, are also presented in Table 3. For the southeast sample, labor productivity increased from .43 units of output per unit of labor for category C1 to 1.31 units of output per unit of labor for category C6. The productivity of capital changes likewise increased from .07 cwt. of hogs per dollar of expenditure for size category C1 to .19 for category C6. For other variable inputs the ratios did not show any appreciable change from one output category to the next.

The ratio Y/X reflected a single factor productivity measure and was calculated to provide a more detailed description of relative factor usage in each sample. From the ratios it appeared that there was a tendency for higher production efficiency of factors as size of unit increased. The understanding of the sources of such improved productivity are confounded without a more thorough specification of the technological changes associated with size changes and the inherent substitution of capital for other inputs, especially labor.

Procedure Used to Measure Firm Technical Efficiency

Two frontier function approaches to measuring firm level technical efficiency were used in this study. One approach used linear programming procedures to calculate total factor productive efficiency relative to a nonparametric production frontier. The alternative frontier approach was a statistical procedure of estimating a stochastic composed error frontier production function of a parameter form. Given this frontier, technical efficiency of a firm was measured as the firm output deviation from the estimated stochastic frontier output. Both approaches measured firm technical efficiency as a one-sided deviation from a modeled production frontier. The two approaches differed in how the production frontier was identified and estimated.

Deterministic Measures of Firm Technical Efficiency

The first approach used was to measure firm technical efficiency in a linear programming formulation. Following the method used by Fare (1983), four technical efficiency measures of each firm in the sample were calculated. The four measures were $K(y,x)$, $W^*(y,x)$, $W(y,x)$, and $F(y,x)$. The first measure, $K(y,x)$ was the original Farrell measure of technical efficiency and was measured relative to a frontier envelope of the data restricted to exhibit constant return to scale and strong input disposability. The second measure, $W^*(y,x)$, was a measure of technical efficiency calculated relative to production frontier modeled to allow a frontier technology exhibiting nonincreasing returns to scale. The third measure, $W(y,x)$ was a measure of technical efficiency calculated relative to frontier modeled to allow for fully variable returns to scale technologies. These three measures, $K(y,x)$, $W^*(y,x)$, and $W(y,x)$, differed only in the scale properties of the modeled frontier. The relationship between these three measures allowed the derivation of a measure of scale inefficiency at the firm level, S(y,x). F(y,x) was a measure of pure technical efficiency calculated relative to a production frontier modeled to exhibit variable return to scale and weak disposability of input. The relationship between W(y,x) and F(y,x) allowed the derivation of structural (congestion) efficiency, C(y,x) at the firm level. F(y,x) was pure technical efficiency devoid of firm inefficiency from scale or structural sources.

All four measures of firm technical efficiency were calculated in this study. Given these, the measures of scale and congestion efficiency were derived. The primary desired products from the linear programming approach were the measures of technical efficiency at the firm level, K(y,x), $W^*(y,x)$, W(y,x), and F(y,x), each calculated with reference to a different assumption about the frontier properties. The measures of scale efficiency and congestion efficiency are summarized and discussed specifically in light of the decomposition of Farrell technical efficiency to its purely technical, scale and structural components.

The Farrell measure of firm technical efficiency was calculated by solving the linear programming problem, K(y,x) shown below.

Problem 1:

$$K(y,x) = \min. \theta$$

$$\text{S.T.} \quad 1)\ ZY_1 + ZY_2 + \ldots + ZY_K \geq Y^0/\theta$$

$$2)\ ZX_{11} + ZX_{12} + \ldots + ZX_{1K} \leq X_1^0$$

$$3)\ ZX_{21} + ZX_{22} + \ldots + ZX_{2K} \leq X_2^0$$

$$4)\quad ZX_{31} + ZX_{32} + \ldots + ZX_{3K} \leq X_3^0$$

$$5)\quad ZX_{41} + ZX_{42} + \ldots + ZX_{4K} \leq X_4^0$$

$$6)\quad Z_i > 0$$

where Variable Y, (Y_1 to Y_K) was the annual output of market hogs for each firm in the sample. Y^0 was the output of the objective firm whose efficiency was being measured. The variables Z and θ (theta) were unknowns. θ was included in the objective function to measure the proportional expansion of the objective firm's output required to bring this firm up to frontier levels of output. Variables X_{1i} thru X_{4i}, i = (1,2,...,K), were the resources used by each hog enterprise in the sample. The variable X_{1i} was labor input, X_{2i} was feed input, X_{3i} was capital input, and X_{4i} was miscellaneous production expenditure inputs. The variables X_1^0 thru X_4^0 were the resource usage by the objective hog farm that produced output Y^0. These terms for the above linear programming problem were the same for the remaining three linear programming problems described below that measure technical efficiency, but with less restrictive frontier specification.

The technical efficiency measure $W^*(y,x)$ was calculated by solving the linear programming problem below. The solution to this problem was a measure of total factor technical efficiency relative to a modeled production frontier exhibiting non increasing returns to scale.

Problem 2:

$$W^*(y,x) = \min.\ \theta$$

$$\text{S.T.}\quad 1)\quad ZY_1 + ZY_2 = \ldots + ZY_K \geq Y^0/\theta$$

2) $ZX_{11} + ZX_{12} +\ldots+ ZX_{1K} \leq X_1^0$

3) $ZX_{21} + ZX_{22} +\ldots+ ZX_{2K} \leq X_2^0$

4) $ZX_{31} + ZX_{32} =\ldots+ ZX_{3K} \leq X_3^0$

5) $ZX_{41} + ZX_{42} +\ldots+ ZX_{4K} \leq X_4^0$

6) $Z_i > 0;\ \Sigma_i^k Z_i \leq 1$

The third variation of firm technical efficiency measurement using the Farrell-Fare linear programming approach was W(y,x). It was calculated by solving the linear programming problem shown below. W(y,x) was calculated relative to a modeled frontier that can exhibit variable returns to scale technologies. This problem formulation will result in the closest frontier envelope fit to the input-output coordinates of the firm.

Problem 3:

$W(y,x) = \min.\ \theta$

S.T. 1) $ZY_1 + ZY_2 +\ldots+ ZY_K \geq Y^0/\theta$

2) $ZX_{11} + ZX_{12} +\ldots+ ZX_{1K} \leq X_1^0$

3) $ZX_{21} + ZX_{22} +\ldots+ ZX_{2K} \leq X_2^0$

4) $ZX_{31} + ZX_{32} =\ldots+ ZX_{3K} \leq X_3^0$

5) $ZX_{41} + ZX_{42} +\ldots+ ZX_{4K} \leq X_4^0$

6) $Z_i > 0;\ \Sigma_i^k Z_i \leq 1$

The above three linear programming problems used to calculate firm technical efficiency differed from one another only by the type of scale properties embodied in the production frontier envelope. As the model allowed the frontier envelope to exhibit more general and variable scale technologies, the technical efficiency of each hog farm was expected to increase as the frontier was fit closer to the data and each firm's output was closer to the frontier levels. By comparing the three technical efficiency measures $K(y,x)$, $W^*(y,x)$ and $W(y,x)$ for a single hog farm, the firm measure of scale inefficiency was derived. Scale inefficiency defined as the ratio $S(y,x) = K(y,x)/W(y,x)$ exists if $S(y,x) < 1$. This was interpreted as a type of technical inefficiency and was measured as lost output due to production at nonconstant returns to scale technology.

The nature of the firms' scale inefficiency attributed to increasing or decreasing scale return technologies provided information for describing the shape of the VRS production frontier. If scale inefficiency exists, $S(y,x) < 1$ and $K(y,x) = W^*(y,x)$, then the scale inefficiency was due to increasing returns frontier technology. If $S(y,x) < 1$ and $K(y,x) < W^*(y,x)$ then scale inefficiency was due to decreasing return to scale frontier technology. For the cross section sample arranged by size of hog output, the kinds and frequencies of the scale inefficiencies that existed implied the shape of the production frontier.

The fourth measure of firm technical efficiency was $F(y,x)$.This measure of firm technical efficiency was the solution to the linear programming problem shown below. This problem, like problem $W(y,x)$, modeled a frontier allowing for variable scale return frontier technologies but was even less restrictive by allowing for weak disposability of inputs.

Problem 4:

$$F(y,x) = \min.\ \theta$$

$$\text{S.T.}\quad 1)\quad ZY_1 + ZY_2 + \ldots + ZY_K \geq Y^0/\theta$$

$$2)\quad ZX_{11} + ZX_{12} + \ldots + ZX_{1K} - X_1^0(\sigma) = 0$$

$$3)\quad ZX_{21} + ZX_{22} + \ldots + ZX_{2K} - X_2^0(\sigma) = 0$$

$$4)\quad ZX_{31} + ZX_{32} + \ldots + ZX_{3K} - X_3^0(\sigma) = 0$$

$$5)\quad ZX_{41} + ZX_{42} + \ldots + ZX_{4K} - X_4^0(\sigma) = 0$$

$$6)\quad \sum_{i=1}^{k} Z_i = 1$$

$$0 < \sigma < 1$$

An assumption allowing for weak disposability of input was modeled to allow some firms to be efficient even if the firm was operating in stage three of the production function with some inputs or set of inputs. If some assets are fixed to the firm then this may be an appropriate assumption. The difference between W(y,x) which modeled variable returns frontiers and strong disposability, and F(y,x) which modeled variable returns but weak disposability, establishes the Fare measure of structural inefficiency called congestion, C(y,x). Congestion inefficiency was defined as C(y,x) = W(y,x)/F(y,x), and was interpreted as a type of inefficiency measured as lost output due to lack of strong input disposability.

The technical efficiency measure F(y,x) was considered to be a measure of pure technical efficiency separate from the other sources of firm technical efficiency. All 4 measures, K(y,x), W^*(y,x), W(y,x) and F(y,x) will be used in further analysis presented in later procedures. Aside from obtaining the measures of technical efficiency, K(y,x), W^*(y,x), W(y,x) and F(y,x), the derived measures of scale congestion inefficiency complete the decomposition of Farrell efficiency into its technical, scale and structural components. The multiplicative relationship was as follows: $K(y,x) = S(y,x) \cdot C(y,x) \cdot F(y,x)$. The Farrell technical efficiency measure was the product of scale inefficiency, congestion efficiency and pure technical efficiency.

Stochastic Frontier Measures of Firm Technical Efficiency

In addition to measuring hog firm technical efficiency by the Farrell-Fare linear programming approach, this study will include an alternative frontier approach. The alternative approach was a statistical estimation of a stochastic production frontier to serve as reference for technical efficiency measurement. This approach followed the method used by Aigner, Lovell, and Shmidt (1977) to identify the stochastic production frontier and the methods proposed by Jardrow et al. (1983) to take the result of a stochastic composed error model estimation and to calculate an observation specific measure of technical efficiency.

To construct a measure of productive (technical) efficiency, the starting point was established by assuming a maximum flow of hog output that any hog farm can attain with a given flow of productive resources.

Following production theory, a production function relationship was specified to relate a hog enterprises' maximum potential output to the observable factor inputs, labor, feed, capital flow, etc., in a statistical formulation. The production function to be estimated was of the form:

$$\ln Y_i^P = B_o + B_1 \ln L_i + B_2 \ln F_i = B_3 \ln C_i + B_4 \ln ME_i + V_i \tag{7}$$

where i = 1,2...,N. The variable $\ln Y_i^P$ represented the hog farm's potential output in cwt. of market hogs. On the right hand side of equation (7) were the determinants of potential output. The variable L_i was annual labor input for the hog enterprise for the ith firm. Variable F_i was the annual feed input. Variable C_i was the annual capital flow associated with the hog enterprise's depreciable assets, and ME_i was the input of miscellaneous production expenditures including fuel oils and electricity. The term V_i was a disturbance, distributed as $N(0,\sigma_v^2)$. Equation (7) was consistent with other production function models studies and the set of logical independent variable factors were specified from an understanding of swine production activities.

Because the hog producer does not have full information regarding the productivity of production technologies available and because the marginal cost of acquiring full information and making short-term adjustments to new techniques and methods generally slope upward, the hog enterprise actual output, Y_i^O, could be expected to be lower than the potential output Y_i^P. Specifically, the usual case is

$$Y_i^O \leq Y_i^P \tag{8}$$

The differences between Y_i^O and Y_i^P will vary across individual hog enterprises depending on the productivity of the technical activities of hog production and the managerial skills of the operator. Presumably, the more productive the production practices and methods used and the better management inputs are, the greater the chance the enterprise has to produce maximum potential levels of hog output (Y_i^P) given the resources employed. The extent to which the potential output (Y_i^P) was not achieved, reflected the technical inefficiency of resource use on the hog farm.

Rewriting equation (8) as

$$Y_i^O = Y_i^P + U_i, \tag{9}$$

where $U_i \leq 0$, and we can see that if $U_i = 0$ then the production would be equal to potential output levels, ($Y_i^O = Y_i^P$).
On the other hand, if $U_i < 0$, production would be less than full potential output levels.

By substituting equation (7) into equation (9), the following expression can be derived:

$$\ln Y_i^O = B_0 + B_1 \ln L_i + B_2 \ln F_i + B_3 \ln C_i + B_4 \ln ME_i + e_i \tag{10}$$

where $e_i = V_i + U_i$ represents the composed error in the function. Equation (10) indicates not only that actual outputs are a function of observable factor inputs and that outputs vary from firm to firm, but also that actual output may equal or fall short of potential "frontier" levels. The extent of this failure reflects technical inefficiency. The one-sided error term U_i, which is a component of the error term e_i of equation (10) quantifies the role of technical inefficiency as a determinant of the differences in output observed in a sample of hog farms.

Equation (10) above will be estimated by a maximum likelihood techniques. Recall that: *

$$e_i = V_i + U_i$$

where

$$V_i \sim N(0, \sigma_V^2)$$

and

$$U_i \leq 0 \text{ such that } U_i \sim N(0, \sigma_U^2) \text{ truncated at zero.}$$

Using the method presented by Aigner, Lovell, and Schmidt (1977), the distribution of e_i can be parameterized as the joint density function:

$$f(e) = \frac{2}{\sigma} f\left(\frac{e}{\sigma}\right)\left[1 - F(e\lambda\sigma^{-1})\right] \tag{11}$$

where

$$\sigma^2 = \sigma_u^2 + \sigma_V^2 , \tag{12}$$

$$\lambda = \frac{\sigma u}{\sigma V} \quad , \tag{13}$$

and f and F in (11) are respectively the standard normal density and distribution functions. The expected value of the composite error e_i is:

$$E(e_i) = E(u_i) = -\frac{\sqrt{2}}{\sqrt{\pi}} \quad \sigma u \tag{14}$$

the mean of the one-sided term. If it is correct to assume that E(u) depicts technical inefficiency in the hog production enterprise, then an estimate of E(u) is required for technical efficiency measurement.

Such an estimate can be obtained by maximum likelihood estimation. The relevant log likelihood function is identical to that used by Aigner, Lovell, and Schmidt (1977). The likelihood function is:

$$\ln L(Y_i \mid \beta_K, \lambda, \sigma^2) = N\ln \frac{\sqrt{2}}{\sqrt{\pi}} + N\ln\sigma^{-1} \tag{15}$$

$$+ \sum_{i=1}^{N} \ln[1-F(e_i\lambda\sigma^{-1})] - \frac{1}{2\sigma^2} \sum_{i=1} e_i^2 \quad .$$

From equation (15) estimates for β, λ, σ^2 can be obtained.

With estimates of λ and the error variance of the model, σ^2, the expected value of the error term E(e) = E(u) can be calculated using equation (14). This expected value is the mean of the one-sided term and hence an estimate of technical efficiency for the sample.

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The techniques of Jondrow et al. (1982) were used to obtain specific estimates of u_i. Their technique used the conditional distribution of u given e to obtain information about u. Because λ, σ_u^2, and σ_V^2 are parameters obtained from the estimation of the likelihood function, equation (15), and e_i can be computed for each observation, and mean values of u on an observation by observation basis can be obtained by evaluating the expression of u below:

$$(16) \qquad E(u_i \mid e_i) = \frac{\sigma_u^2 \sigma_V^2}{\sigma^2} \frac{f(e_i \lambda/\sigma}{1-F(e_i \lambda/\sigma)} - \frac{e_i \lambda}{\sigma}$$

compare to Lindsay

Because $u_i \leq 0$, this estimate indicates the amount by which a particular observation is producing relative to its stochastic frontier output level. To identify the relevant stochastic frontier output level, the absolute value of the estimate of u_i^P is added to actual output, thus giving (Y_i) potential maximum output $Y_i^O + |u| = Y_i^P$. Technical efficiency is measured for each firm in the sample as Y_i^O/Y_i^P, actual output over expected maximum potential output.

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why ||?

Explaining the Variation in Technical Efficiency

The measurement of technical efficiency (TE) as addressed in the first objective provided a basis for comparison of observations. To summarize simply the relative magnitude of technical inefficiency observed in a sample of hog farms would provide little or no basis for needed firm adjustment. A more meaningful comparison would be the logical use of this information to investigate the relationship between production practices and technical efficiency (Timmer, 1971; Farrell and Fieldhouse, 1962; Byrnes, 1985; Meller, 1976; Seitz, 1971; Burley, 1980). It was proposed here to explain the variation in technical efficiency within the cross-section of observations by regressing specific production methods and practice variables on the dependent variable technical efficiency (TE). A general linear model will be fit to the data using ordinary least squares techniques.

The variation in estimated technical efficiency observed in the sample was hypothesized to be related to observed hog farm production methods and practices. The selection of these variables was based on an understanding of swine production technical relationships at work in the production process.

The general linear explanatory models will be in the form:

$$\text{(17)} \quad T.E. = b_0 + b_1PI + b_2ECS1 + \ldots + b_6ECS5 + b_7M_2 + b_8B_1 + \ldots + b_{10}B_3 + b_{11}MN_2 + \ldots + b_{13}MN_4 + b_{14}CF_1 + \ldots + b_{17}CF_4 + E.$$

Ten models of the above specification were estimated using regional data. Eight models (four for each region) had as the dependent variables the technical efficiency measures K(y,x), W(y,x), $W^*(y,x)$ and F(y,x) as generated by the linear programming approach (TE_{LP}). Two models, (one for each region), had dependent technical efficiency estimated using the stochastic composed error approach (TE_{CE}). The objective was to relate hog enterprise production practices and techniques with technical efficiency.

Measurement and Logic of Explanatory Variables

Technical efficiency could be expected to be related to both structural characteristics of the hog enterprise and the productivity of the resources employed. Analysis of technical efficiency should then render some insight regarding what are some of the manageable sources of technical inefficiency. A relevant question is which production practices employed in hog enterprises appear to bear a significant relationship to technical efficiency.

The explanatory regression models applied to each regional sample were designed to explain the variation in the dependent technical efficiency measures. Each model contained a common set of dummy variables that indicated the use or nonuse of certain kinds and levels of production practices. The dummy groups were: environmental control (ECS1-ECS5), type of business organization (B_1-B_3), type of management (M_1, M_2), method of handling manure wastes (MN_2-MN_4), and feed processing and feeding method (CF_1- CF_4). Additionally, each model included a continuous variable that measured the production intensity (PI).

The independent variables were:

1. Continuous variable

$$PI = \frac{\text{Total head marketed}}{\text{Expected sow herd size (ESS)}}$$

where: ESS = Annual litters/expected farrowing frequency (EFF)

where: EFF was given by the weaning age of the pigs.

Variable PI was a continuous variable. The logic behind this variable specification was based on the relationship between the sow herd farrowing frequency and the intensity of use of the farrowing facilities and equipment. Given a fixed total herd size and fixed facility and equipment assets, if the sow produced more litters of pigs per year, housing and equipment were used with either a higher frequency and/or filled to a higher capacity. Earlier weaning of pigs allowed the sow to be rebred sooner and to produce more litters annually.

It was hypothesized that as farrowing facilities were used more intensely, as indicated by farrowing frequency, that other stages of production (finishing, breeding, nursery, etc.) were also used with comparable intensity. Thus it was postulated that the measure of sow farrowing frequency adequately indexes the associated intensity of production throughout each subsequent production phase prior to marketing.

Variables ECS0,..., ECS5 were (0,1) dummy variables that indicated the incidence of total confinement in up to five different phases of the production process (breeding, gestation, farrowing, nursery and finishing). This variable group was expected to indicate the level of environment control in the production process. This concept was indicative of the degree to which the hog production processes have moved away from land and labor intensive systems and toward capital intensive systems of production in the form of mechanization of production chores or use of energy intensive facilities and equipment.

Thus, we can expect complimentary sets of labor saving technologies for feeding, health programs and waste handling to supplement production in environment control situations. Given this relationship, the use of total confinement in up to all five phases of the production process served as an index of the level of environment control used in the hog enterprise.

ECS1 = 1 if environment control in 1 of 5 phases
= 0 otherwise

ECS_2 = 1 if environment control in 2 of 5 phases
= 0 otherwise

ECS3 = 1 if environment control in 3 of 5 phases
= 0 otherwise

ECS4 = 1 if environment control in 4 of 5 phases
= 0 otherwise

ECS5 = 1 if environment control in 5 of 5 phases
= 0 otherwise

ECS6 = 1 if environment control does not apply
= 0 otherwise

Variables M_1, M_2 were (0,1) dummy variables included to indicate the incidence of hired management used in the hog enterprise. The hypothesis was that hired managers contributed higher quality labor and management skills than unpaid family or hired labor inputs and influenced the technical productivity of each productive factor.

M_1 = 1 if hired management applied to the observation
= 0 otherwise

$M_2 = 1$ if no hired management

$= 0$ otherwise

Variables $B_1, \ldots, B_4$ are (0,1) dummy variables that represented five possible types of business organizations. The hypothesis was that the technical efficiency of observations may be related to the organizational structure of the farm business. There were four types represented by these variables:

$B_1 = 1$ if partnership

$= 0$ otherwise

$B_2 = 1$ if corporation

$= 0$ otherwise

$B_3 = 1$ if cooperative

$= 0$ otherwise

$B_4 = 1$ if individual operator

$= 0$ otherwise

Variables $MN_1, \ldots, MN_4$ were (0,1) dummy variables that indicated the method of handling manure wastes from the hog enterprise. Methods of handling manure varied from not being handled to being handled in solid, liquid or solid and liquid forms. The relationship between manure handling methods and productivity (resource use) of the implied technology of a waste management system may reveal an important consideration for production planning.

$MN_1 = 1$ if manure is not handled

$= 0$ otherwise

MN_2 = 1 if manure is handled in solid form

= 0 otherwise

MN_3 = 1 if manure is handled in liquid form

= 0 otherwise

MN_4 = 1 if manure is handled in solid and liquid form

= 0 otherwise

Variables CF_1, ..., CF_5 were (0,1) dummy variables. This group of variables indicated the form and method of processing feeds used for the hog enterprise. The methods varied from the separate feeding of grains and supplements to the use of complete feed formulation provided by custom services. This characteristic of the hog production enterprise was expected to affect both animal performance and resource use.

CF_1 = 1 if complete feed purchased

= 0 otherwise

CF_2 = 1 if complete feed formulated on the farm with portable grinder and mixer

= 0 otherwise

CF_3 = 1 if complete feed formulated on the farm with stationary electric grinder and mixer

= 0 otherwise

CF_4 = 1 if complete feed custom formulated on the farm

= 0 otherwise

CF_5 = 1 if grain and supplement are fed separately

= 0 otherwise

As formulated the models postulated a continuous relationship between intensity of production and technical efficiency. For each dummy variable group one variable class was omitted from the model to prevent singularity and to permit estimation of coefficients. Since no interaction term was included for the dummy variables, the estimated coefficients can be interpreted only in terms of the effect on the intercept of the function (not the slope). For each variable in the model the null hypothesis was that Ho: $b_1,\ldots,b_{17} = 0$.

CHAPTER IV

RESULTS OF ANALYSIS

Deterministic Measures of Firm Technical Efficiency

The first type of technical efficiency measurement applied to the 1980 cost of production of hogs enterprise data was a deterministic approach. Measures of technical efficiency were obtained as solutions to linear programming problems. The linear programming solutions were multi factor productivity measures of technical efficiency measured as the strictly one-sided deviation from a production frontier. The distance from the frontier was measured in output terms. This allowed enterprise technical efficiency to be expressed as a ratio of actual to potential output.

For the deterministic approach, four different linear programming models were constructed. Each model measured multi-factor technical efficiency, but differed in the type of reference technology embodied in the production frontier. Initially three variations in scale properties of the frontier technology were assumed and modeled and technical efficiency for each enterprise (observation) was measured. The first three technical efficiency measures, K(y,x), W*(y,x) and W(y,x) were based on varying assumptions; constant returns to scale, nonincreasing returns to scale, and variable returns to scale, respectively. From these three technical efficiency measures for each observation one can derive a measure of scale inefficiency S(y,x), calculated as the ratio K(y,x)/W(y,x), which when less than 1, indicated that the hog enterprise was operated in an output range where the frontier envelope of the observation exhibited increasing, constant or decreasing returns to scale. Each of the first three technical efficiency measures K(y,x), W*(y,x) and W(y,x) assumed strong input disposability in the frontier production technology. Estimates of pure technical efficiency, F(y,x) were obtained by solving the fourth type of linear programming problem which was a further relaxation of scale and input disposability properties of a production frontier. F(y,x) was calculated relative to a production frontier modeling variable returns to scale like W(y,x), but differed by modeling weak input disposability or stage III production with some input. Structural inefficiency--lack of strong input disposability (congestion), was measured by comparing solutions to problem 3, W(y,x) and problem 4, F(y,x) for each observation. Input congestion, calculated as W(y,x)/F(y,x), was a component of enterprise efficiency and was a source of inefficiency related to asset fixity and not part of pure technical efficiency hypothesized as associated with production practices and techniques.

Comparisons of Technical Efficiency Estimates Among Regions and Firm Size

The means of the four technical efficiency measures K(y,x), W*(y,x), W(y,x) and F(y,x) for each regional cross sectional sample of hog enterprises are shown in Tables 4 and 5. Some general characteristics of the results were noteworthy. First, and probably most noticeable, was that for each output category and for each entire

Table 4. Means and standard deviation of linear programming estimates of technical efficiency for the north central sample of farrow-finish hog units.

Tech. Eff.	Stats.	C1 N = 20[b]	C2 N = 40	C3 N = 42	C4 N = 48	C5 N = 45	C6 N = 21	Overall Sample N = 216
		Annual Output Category[a]						
K(y,x)	$\bar{X}$	0.7486	0.7957	0.7810	0.7979	0.8539	0.8731	0.8077
	st. dev.	0.1417	0.1167	0.1431	0.1110	0.0850	0.1063	0.1221
	C.V.	18.940	14.787	18.332	13.916	9.957	12.185	15.123
W*(y,x)	$\bar{X}$	0.7486	0.7959	0.7836	0.8066	0.8841	0.914	0.8205
	st. dev.	0.1417	0.1174	0.1401	0.1108	0.0819	0.1011	0.1256
	C.V.	18.935	14.757	17.881	13.744	9.269	11.069	15.312
W(y,x)	$\bar{X}$	0.8138	0.8139	0.7841	0.8068	0.8841	0.9142	0.8308
	st. dev.	0.1541	0.1248	0.1401	0.110	0.0819	0.1012	0.1254
	C.V.	18.941	15.334	17.869	13.766	9.279	11.069	15.102
F(y,x)	$\bar{X}$	0.8710	0.8396	0.7927	0.8229	0.9009	0.9387	0.8517
	st. dev.	0.1703	0.1326	0.1431	0.1214	0.0848	0.0873	0.1313
	C.V.	19.559	15.797	18.059	14.754	9.421	9.301	15.417

[a]C1 = 100-199 head C4 = 1000-1999 head
C2 = 200-499 head C5 = 2000-4999 head
C3 = 500-999 head C6 = greater than 5000 head

[b]N is the number of firm in each size category.

Table 5. Means and standard deviation of linear programming estimates of technical efficiency for the southeast sample of farrow-finish hog units.

		Annual Output Category[a]						
Tech. Eff.	Stats.	C1 N = 36[b]	C2 N = 68	C3 N = 70	C4 N = 72	C5 N = 66	C6 N = 27	Overall Sample N = 339
K(y,x)	$\bar{X}$	0.6694	0.6775	0.7053	0.6917	0.7056	0.7901	0.6990
	st. dev.	0.1483	0.1483	0.1578	0.1313	0.1274	0.1392	0.1444
	C.V.	22.164	21.893	22.374	18.984	18.061	17.626	20.671
W*(y,x)	$\bar{X}$	0.6710	0.6823	0.7238	0.7213	0.7510	0.8953	0.7274
	st. dev.	0.1483	0.1482	0.1579	0.1328	0.1339	0.1260	0.1526
	C.V.	22.108	21.722	21.822	18.414	17.830	14.074	20.987
W(y,x)	$\bar{X}$	0.7792	0.6996	0.7257	0.7217	0.7513	0.8953	0.7428
	st. dev.	0.1736	0.1506	0.1592	0.1329	0.1334	0.1260	0.1536
	C.V.	22.279	21.537	21.947	18.422	17.759	14.074	20.689
F(y,x)	$\bar{X}$	0.8114	0.7597	0.7676	0.7572	0.8005	0.9553	0.7887
	st. dev.	0.1714	0.1599	0.1640	0.1435	0.1359	0.0073	0.1572
	C.V.	21.124	21.051	21.368	18.592	16.977	8.099	19.931

[a] C1 = 100-199 head C4 = 1000-1999 head
C2 = 200-499 head C5 = 2000-4999 head
C3 = 500-999 head C6 = greater than 5000 head

[b] N is the number of observations in each size category.

regional sample, mean technical efficiencies increased as the production frontier envelope was drawn tighter around the scatter of observations by relaxing scale property restrictions and strong input disposability assumptions. This result was expected since as the frontier restrictions were relaxed the frontier was identified by a larger subset of observations and all observations were nearer frontier levels of productivity. For the north central sample,the frontier measure of technical efficiency K(y,x) averaged 0.8077 while the less restrictive measure F(y,x) averaged 0.8517. Likewise, for the southeast sample, the frontier measure of technical efficiency K(y,x) averaged 0.6990 and the less restrictive measure F(y,x) averaged 0.7887. Each of the four linear programming problems modeled a reference frontier for efficiency measurement and necessarily, each frontier was piecewise linear, i.e., composed of many linear segments,and connected the extreme observations that were technically efficient; (TE = 1.0). For the measure K(y,x),based on a model with underlying constraints of constant returns to scale and strong disposability of inputs, 19 of the 339 observations in the southeast sample were on the frontier. For the measure F(y,x),based on a model which permitted variable returns to scale and weak input disposability, 70 of the 339 observations of the southeast sample identified the frontier. Some farrow to finish hog enterprises, deemed inefficient relative to a CRS-SDI frontier (K(y,x)), were now efficient when measured relative to a less restrictive assumption of a VRS- WDI frontier (F(y,x)). Similarly, for the north central sample, the envelope frontier K(y,x) showed 18 of 216 observations on the frontier; estimates for the F(y,x) model showed 58 of 216 observations on the frontier.

The results also showed that average technical efficiency increased with volume of output. In the southeast sample, estimates indicated that K(y,x) averaged .6694 for output category C1 and K(y,x) averaged .7901 for output category C6. In the north central sample estimates indicated K(y,x) averaged .7486 for output category C1 and .8731 for output category C6. This relationship was evident for all four measures of technical efficiency. In addition to the observed higher technical efficiency for larger output groups, variation around the mean of measured technical efficiency was smaller as size increased. In the southeast sample output category C1 where K(y,x) averaged .6994 the coefficient of variation, C.V., about the mean was 22.164 indicating that 1 standard deviation was approximately 22% of the value of the mean technical efficiency for this category. For the output category C6 where mean K(y,x) averaged .7901 the C.V. was 17.626 indicating that 1 standard deviation about this mean was approximately 17% of the value of the mean for the category. Likewise for the north central sample measure of K(y,x), the coefficient of variation was 18.940 in category C1 and 12.185 for category C6. In each sample, the same was also true for the other TE measures W*(y,x), W(y,x) and F(y,x).

Estimates shown here were indicative of only the technical efficiency component of performance. The overall economic efficiency of the firm would be shown by the product of firm allocative (pricing) efficiency and technical efficiency.

Components of Technical Efficiency

In addition to obtaining observation level multi-factor technical efficiency measures K(y,x), W*(y,x), W(y,x) and F(y,x), the linear programming approach made it possible to decompose the historical Farrell measure of technical efficiency, K(y,x), into its technical, structural and scale components. The four initial technical efficiency measures and the derived measures of scale and congestion inefficiency are shown in Table 6. Scale inefficiency, S(y,x), was measured as lost output when the frontier deviated from a constant returns technology, (S(y,x) $<$ 1.0). Congestion inefficiency C(y,x) was measured as lost output due to stage III production with some input or set of inputs. Comparisons of the derived measures of firm inefficiency showed that neither scale nor congestion inefficiency were very great while pure technical inefficiency of the firm was the largest component of the relationship; $K(y,x) = S(y,x) \cdot C(y,x) \cdot F(y,x)$. For the north central sample, mean scale efficiency averaged 97%, congestion efficiency averaged 97% while pure technical efficiency averaged 85%. For the southeast sample, mean scale efficiency averaged 94%, congestion efficiency averaged 94%, while pure technical efficiency averaged only 78%. As a source of inefficiency to the firm pure technical inefficiency appeared to dominate.

In both regional samples estimates indicated that scale and congestion inefficiency appear to be less for intermediate output

Table 6. Types of computed and derived technical efficiency measures.

Computed Initially	Efficiency Measure	Type of Reference Technology
1.	K(y,x)	CRS-SDI
2.	W*(y,x)	NIRS-SDI
3.	W(y,x)	VRS-SDI
4.	F(y,x)	VRS-WDI
<u>Derived</u>		
5.	S(y,x)	$= \dfrac{K(y,x)}{W(y,x)} \leq 1$
6.	C(y,x)	$= \dfrac{W(y,x)}{F(y,x)} \leq 1$

Decomposition of Farrell K(y,x), Technical Efficiency:

$$K(y,x) = S(y,x) \cdot C(y,x) \cdot F(y,x)$$

categories than for the extreme high or low output categories. This relationship intuitively was consistent with a theoretical production function showing a range of increasing scale economies, followed by constant and then decreasing economies.

For the purpose of this study, the measures of structural inefficiency,(congestion) will be dealt with only in the light of recognizing the Fare decomposition of Farrell technical efficiency into its purely technical, scale and congestion components. Also a derived measure of firm inefficiency, the measure of scale inefficiency, S(y,x) < 1.0 was more interesting for a representation of the shape of the frontier envelope itself. Comparing the measures K(y,x), W*(y,x) and W(y,x) for each observation can reveal the nature of the scale inefficiency S(y,x) < 1 , as due to increasing, decreasing or constant returns frontier technology when scale returns can vary.

The nature of scale inefficiencies for each entire regional sample and for each descriptive output category are shown in Tables 7 and 8. For the southeast, sample enterprise scale inefficiency was due to IRS for 23.3% of the observations, CRS for 6.5% of the observations and DRS for 70.2% of the observations (Table 8). For the north central sample, the frequencies of IRS, CRS and DRS were 39.4%, 8.8% and 51.8%, respectively (Table 7). Thus, estimates indicated that the frontier was not a constant returns frontier throughout the range of the cross-section. Some portion of the production frontier must deviate from CRS where S(y,x) < 1.0. Because the W(y,x) frontier was a piecewise linear frontier, further substantiation for a likely

Table 7. Means and standard deviation of structural and scale inefficiency and type of scale inefficiency for the north central sample of farrow-finish hog units.

Efficiency Measure	Stats.	Annual Output Category[a]						Overall Sample
		C1 N = 20[b]	C2 N = 40	C3 N = 42	C4 N = 48	C5 N = 45	C6 N = 21	N = 216
C(y,x)	$\bar{X}$	0.9407	0.9728	0.9898	0.9828	0.9821	0.9739	0.9776
	st. dev.	0.0837	0.0656	0.0276	0.0421	0.0324	0.0554	0.0504
	C.V.	8.904	6.752	2.794	4.287	3.307	5.688	5.165
S(y,x)	$\bar{X}$	0.9241	0.9792	0.9950	0.9885	0.9657	0.9553	0.9732
	st. dev.	0.0735	0.0334	0.0123	0.0133	0.0337	0.0508	0.0425
	C.V.	7.958	3.414	1.239	1.348	3.494	5.324	4.367
Type of scale ineff. by % of N	IRS	80.0	87.5	50.0	20.8	4.4	4.8	39.4
	CRS	10.0	10.0	11.9	4.2	6.7	14.3	8.8
	DRS	10.0	2.5	38.1	75.0	88.9	81.0	51.8

[a]C1 = 100-199 head C4 = 1000-1999 head
C2 = 200-499 head C5 = 2000-4999 head
C3 = 500-999 head C6 = greater than 5000 head

[b]N is the number of firms in each size category.

Table 8. Means and standard deviation of structural and scale inefficiency and type of scale inefficiency for the southeast sample of farrow-finish hog units.

Efficiency Measure	Stats.	Annual Output Category[a] C1 N = 36[b]	C2 N = 68	C3 N = 70	C4 N = 72	C5 N = 66	C6 N = 27	Overall Sample N = 339
C(y,x)	$\bar{X}$	0.9602	0.9292	0.9486	0.9563	0.9422	0.9370	0.9456
	st. dev.	0.0545	0.1101	0.0783	0.0592	0.0851	0.1044	0.0839
	C.V.	5.772	11.856	8.257	6.193	9.041	11.147	8.880
S(y,x)	$\bar{X}$	0.8685	0.9685	0.9715	0.9580	0.9397	0.8817	0.9437
	st. dev.	0.1084	0.0329	0.0330	0.0310	0.0389	0.0785	0.0617
	C.V.	12.486	3.401	3.403	3.243	4.142	8.907	6.540
Type of scale	IRS	77.8	45.6	18.6	8.3	1.5	0.0	23.3
ineff. by	CRS	8.3	7.4	5.7	1.4	6.1	18.5	6.5
% of N	DRS	13.9	47.0	75.7	90.3	92.4	81.5	70.2

[a]C1 = 100-199 head C4 = 1000-1999 head
C2 = 200-499 head C5 = 2000-4999 head
C3 = 500-999 head C6 = greater than 5000 head

[b]N is the number of firms in each size category.

nonlinear production function was implied by examining the frequencies of IRS, CRS and DRS for each descriptive output size category and specifically how these frequencies change from one output size category to the next. In the southeast sample (Table 8), the frequency of the kinds of scale inefficiency in output category C1 were IRS--77.8%, CRS--8.3% and DRS--13.9%. For C6 the largest size group the frequencies were: IRS--0.0%, CRS--18.5% and DRS--81.5%. The same pattern was evident for the north central sample (Table 7). For category C1 the frequencies for various forms of scale inefficiency were IRS--80.0%, CRS--10.0%, DRS--10.0% .For output category C6 the frequencies were IRS--4.8%, CRS--14.3% and DRS--81.0%. This evidence for the likely nonlinear shape of an unknown true production frontier function could serve as a priori information for choosing a functional form specification in other production function estimations.

Because the four measures of technical efficiency, K(y,x), W*(y,x), W(y,x) and F(y,x) were solutions to deterministic linear programming procedures, no statistical inferences can be made about the resulting solutions. In addition there were no estimates of parameters of the production frontier were obtained. These limitations hinder the description of the frontier production relationship and may detract from their appeal as measures of enterprise performance. The virtue of the linear programming approach lies in its consistency with the original concept of how to measure firm technical efficiency. Also the approach makes it easy to model alternative assumptions about frontier function properties and the ability to provide estimates of pure technical efficiency separate from scale or congestion inefficiency at the firm level. The technical efficiency measures K(y,x), W*(y,x), W(y,x) and F(y,x) for each regional sample were used in later analysis and also served for comparisons with estimates derived from a stochastic approach.

Stochastic Production Function Estimates of Technical Efficiency

The alternative frontier function approach used here to measure technical efficiency of hog enterprises was a statistical modeling approach. The Farrell concept of firm technical efficiency measurement was preserved, but the model was specified as a stochastic production frontier to use as reference for the one-sided efficiency measure. Estimates derived for the stochastic production frontier included both testable parameter coefficient estimates and a composed error term. Technical efficiency was still defined as a one-sided, measure, but the frontier was stochastic and varied randomly across observations in the sample according to a normally distributed two-sided stochastic component of the error term. The stochastic frontier became $[f(X_{i:}B) + V_i]$ where $V_i \sim N(0,\sigma^2)$ and technical inefficiency was derived as a point estimate $E(u_i|e_i)$ of the conditional dis- tribution of u_i where $u_i \sim |N(U,\sigma^2)|$ was truncated at zero. Using the Cobb-Douglas functional form for the frontier production function estimation resulted in a linear function where the sum of the parameter coefficient estimate implied a homogeneous scale relationship. The attributes of the Cobb-Douglas functional form are well recognized, but somewhat secondary to this analysis. The important reasoning for the modeling of a production frontier, using the composed error framework, was not only to obtain estimates for the parameters of the production frontier but to decompose the error structure into its normally distributed component, such that the frontier would be stochastic, and so that the one-sided distribution could be assumed to contain the measure of firm technical inefficiency.

The results of the regression analysis are shown in Table 9. Separate estimates were obtained for each regional sample of hog enterprises. All the parameter coefficient estimates were of the correct positive sign indicating that each productive factor bears a positive functional relationship in determining output of market hogs. The R^2 measures of model fit were quite high for each region. Corrected Ordinary Least Squares (COLS) estimates are shown for each region. For the southeast sample, however, in addition to the composed error estimates from the COLS technique a Maximum Likelihood Estimate was obtained to get more consistent and efficient parameter coefficient estimates. For the north central sample, COLS results showed that except for the labor variable, all regression coefficients were significantly different from zero at the 95% confidence level. The estimated labor coefficient, was considerably higher in the Southeast Region than in the North central Region while the estimated coefficient for miscellaneous expense was substantially higher in the North Central Region. Estimated coefficients for feed and capital variables were

Table 9. Stochastic frontier production function parameter estimates for the models of the southeast and north central regions.

	Region			
	North Central		Southeast	
Variable	COLS[c]	MLE[d]	COLS	MLE
Intercept	715.50 (4.90)[a]	--	1676.26 (15.86)	860.22 (8.46)
Labor	0.0199 (0.43)	--	0.2209 (7.98)	0.2407 (8.70)
Feed	0.1606 (24.35)	--	0.1479 (31.39)	0.1776 (29.10)
Capital	0.0096 (3.43)	--	0.0153 (4.68)	0.0087 (2.96)
Misc.[b] Exp.	0.0909 (9.37)	--	0.0243 (6.35)	0.0167 (5.44)
	R^2 = 0.9430		R^2 = 0.9508	

[a]t-ratios are in parentheses.

[b]Miscellaneous expenditures for veternary services, fuel, lubricants, and custom services.

[c]Corrected ordinary least squares estimates.

[d]Maximum likelihood estimates.

similar in the two regions. Maximum Likelihood Estimates for the Southeast Region were not greatly different from COLS estimates.

The central concern here was not the parameters of the frontier itself, but the composition of the error disturbance term which contained not only the random component of the stochastic production frontier, (V_i) but also the estimate of the firm technical inefficiency. Descriptive statistics for the composed error term, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ are shown in Table 10 for each regional stochastic frontier model. Total error variance, σ^2 was larger for the southeast region sample than for the north central sample, but total error variance was roughly proportional to the sample size in the two regions. The extent of technical inefficiency that exists among the farmers in the sample, can be judged by comparing the relative magnitude of the component error terms σ_v^2 and σ_u^2. The statistic lambda, λ, a ratio of these two error components showed at least in a general sense the extent of technical inefficiency for the samples. Lambda (λ) was defined as σ_u/σ_v. For the southeast sample, $\lambda = 2.38$. For the north central sample $\lambda = 0.41$. Relative to the variation in the frontier overforms (given b's and σ_r^2) the variations of observed output beneath the frontier output (given b's and σ_u^2) was much greater in the Southeast than in the North Central sample of firms. The one-sided component of the error term was larger than the normally distributed two-sided component. For the north central sample, just the reverse was indicated. The ratio was less than one indicating that the one-sided distribution was only a fraction of the size of the two-sided normally distributed component. Because firm level estimates of technical inefficiency were obtained from the distribution of the one-sided error component u_i, it was logical to expect that technical efficiency values for the southeast sample were distributed over a broader range of values than for the north central sample, and that the average technical efficiency of firms would be higher in the north central sample.

Table 10. Summary measures of the composed error term of the stochastic production frontier model for each regional sample of hog units.

Composed Error Parameter	Southeast[a] ML Estimate	North Central[b] COLS Estimate
σ^2	3,847,454 (9.00)[d]	2,616,346
λ^c	2.3815	0.4192
σ_u^2	3,270,766 (6.82)	391,111
σ_v^2	576,687 (5.20)	2,225,236

[a]Estimates obtained by Maximum Likelihood Estimation Technique.

[b]Estimates obtained by Corrected Ordinary Least Squares Technique.

[c]λ is σ_u over σ_v, where u_i is one-sided.

[d]t-Ratios are in parentheses.

From the regression procedures, estimates of betas, lambda (λ), and error variance (σ^2) were obtained. Knowledge of λ and σ^2 made it possible to estimate the expected mean of the one-sided error term u_i and in turn to estimate the degree of technical inefficiency for the sample. Using the techniques developed by Jandrow et al. (1982) specific estimates of u_i for each observation were obtained. This approach which assumed a conditional distribution of u_i given e_i was used to obtain mean values of u_i on a observation by observation basis. The estimates of u_i drawn from the assumed conditional distribution provided the shortfall in the production of hogs relative to the stochastic frontier levels of production for each observation. Technical efficiency for each firm was calculated relating actual output to expected frontier output, $Y_i/[Y_i + |E[u_i|e_i]|]$. Average values of technical efficiency for a subset of a full sample were obtained using simple arithmetic means. Technical efficiency estimates are shown in Table 11 for both the North Central and the Southeast samples. The measures of technical efficiency were expressed as a ratio of actual output to expected frontier output. The ratio is given as a decimal proportion with perfect technical efficiency equal to 1.0.

Mean technical efficiency was 0.6203 for the southeast sample and 0.7832 for the north central sample. The most notable feature of these results were the wide range in technical efficiency across the size groups and in both regional samples. For the southeast, the average technical efficiency for subset output category C1 was 0.2534, increasing to 0.9150 for the subset output category C6. For the north central sample of hog enterprises, average technical efficiency for subset C1 was 0.4074 improving to 0.9745 for the subset of hog

Table 11. Means and standard errors of the stochastic frontier estimates of technical efficiency for the north central and southeast sample of farrow=finish hog units.

	Region			
	Southeast		North Central	
Output Category[a]	n	Mean of TE[b]	n	Mean of TE
Sample	339	0.6203 (0.122)[c]	216	0.7832 (0.0120)
C1	36	0.2534 (0.0057)	20	0.4074 (0.0110)
C2	68	0.4113 (0.0093)	40	0.6101 (0.0115)
C4	72	0.7296 (0.0108)	48	0.8709 (0.0033)
C5	65	0.8432 (0.0127)	45	0.9355 (0.0029)
C6	23	0.9150 (0.0215)	21	0.9745 (0.0030)

[a]C1 = 100-199 head C4 = 1000-1999 head
C2 = 200-499 head C5 = 2000-4999 head
C3 = 400-999 head C6 = greater than 5000 head

[b]$TE = Y_i/[Y_i + |E(u_i|e_i)|]$

[c]Standard errors are in parentheses.

enterprises in output category C6. The tendency for technical efficiency to increase as we move across output categories in the cross- sections may have been in part due to the type of model specified to represent the frontier function. The Cobb-Douglas functional form specification of the production frontier was unable to represent variable scale economies across the output range of the cross sectional sample, leaving some observation farther removed from the frontier than they would be if the frontier had the unrestricted shape of a theoretical production function.

Comparisons of the Two Frontier Functions Approaches to Technical Efficiency Measurement

Firm level technical efficiency was estimated using both the "Farrell" linear programming approach and also the "Fare" modifications which permitted relaxing the restrictive frontier properties of constant returns to scale and strong input disposability. These modifications in the linear programming problems allow the original "Farrell" technical efficiency measure, K(y,x), to be decomposed into its purely technical, scale, and congestion inefficiency components. To the extent that scale inefficiency was indicated, the frequency of the types of scale inefficiency gave an indication of the shape of the VRS frontier. Technical efficiency was also estimated using a random stochastic production frontier which was used to evaluate the firm's technical performance. Both approaches were consistent with the original Farrell concept of measuring firm level technical inefficiency as the failure to achieve potential or expected frontier levels of productivity. Intuitively a frontier function capable of modeling variable scale properties would be an improvement over the restrictive Farrell frontier and would be reasonable for application to production activities that are likely to exhibit empirically this type of variation. In solving the four linear programming problems for firm technical efficiency, a necessary result of varying the assumption about scale restrictions on the frontier was that as the frontier was drawn to include more outliers of the data the relative technical efficiency of any firm was improved. This was true because each firm was now closer to the frontier when variable scale returns frontier properties were permitted. In fact, the less restrictive frontiers of problem 3 and 4 allowed the largest subset of the empirical data to dictate the shape of the frontier and, at least, a general notion that the frontier shape was dominated by DRS technologies was revealed through the measure of firm scale inefficiency S(y,x). If the true frontier relationship of some cross section of hog enterprises is assumed to exhibit variable scale returns, then a linear program modeling that allows the frontier to assume some unrestricted shape would give estimates of technical efficiency unconfounded by the errors of an overly restrictive frontier assumption.

The justification for the stochastic frontier-composed error modeling approach was based on the notion that the measure of firm technical efficiency should be devoid of random stochastic disturbances that are not under management control. The procedures involved specifying a production function with a composed error term made up of a normally distributed error component that identified the stochastic frontier. The remaining one-sided component described the firm production shortfall relative to the expected frontier output. In this case the firm's measure of technical inefficiency was distinguished from other sources of output variation. The common homogeneous Cobb-Douglas functional form was used to estimate the stochastic production frontier for the data, as the composed error specification leading to estimates of technical efficiency was of primary interest. The Cobb-Douglas function estimates indicated a DRS frontier technological relationship for both regional samples. Mean levels of technical efficiency for each region were similar to those obtained for the CRS frontier measure, K(y,x), of the linear programming approach.

Regression Results of Explanatory Models of Firm Technical Efficiency

The second objective of this study was to use the measurements of enterprise level technical efficiency in an explanatory analysis directed at identifying possible sources of this inefficiency under management control. If one assumes that technical inefficiency exists and was measurable at the firm level and was in part responsible for firm to firm variation in output, then the real value of technical efficiency measurement would be in identifying specific farm production characteristics that were related to the relative technical efficiency level. This may be important in at least two respects. First, through this type of exploratory analysis, a population of hog farms might be better described if one knows which production techniques tend to result in improvements in technical efficiency. Describing farms in this fashion might also provide information about the firm that can be used to identify homogeneous technologies prior to production function research. In the second place, results may have enterprise level interpretation and serve some pragmatic purposes in planning and management of hog production activities.

Descriptive characteristics of the hog production activity proposed as explanatory variable included production intensity, environment control use, type of business organization, management types, feed processing and feeding techniques, and manure handling techniques. The hypothesized relationships were tested using a general linear model and regressing the independent variables describing production practices and techniques on the dependent technical efficiency measure. Five explanatory models were constructed for each regional sample of hog enterprises. Each model had a common set of independent regressors. The five models differed in the type of technical efficiency measure used as the dependent variable. The five dependent variables and associated underlying characteristics are shown in Table 12. Linear programming measures procedures were used to estimate technical efficiency for models 1, 2, 3, and 4. The technical efficiency measure used for model 5 was a statistical measure.

The common set of independent regressors specified as explanatory variables included one continuous variable, PI, and five groups of dummy variables. The independent explanatory variables are shown below in Table 13.

Table 12. Technical efficiency estimates used as dependent variables in explanatory regression models.

Model	Technical Efficiency Measure	Frontier Type
1	K(y,x)	CRS[a]-SDI[d]
2	W*(y,x)	NIRS[b]-SDI
3	W(y,x)	VRS[c]-SDI
4	F(y,x)	VRS-WD[e]
5	Yi/Yi	g(Xi:B) + Vi (stochastic)

[a]CRS is constant returns to scale
[b]NIRS is nonincreasing returns to scale
[c]VRS is variable returns to scale
[d]SDI is strong disposability of inputs
[e]WDI is weak disposability of inputs

Table 13. Explanatory variables used in regression models of firm technical efficiency.

1. PI: Production Intensity - continuous variable

Dummy Variable group	Variables	Omitted Class
2. Envir. Control (6)	ECS1-ECS5	ECS0: No Envir. Control
3. Management Type (2)	M_2	M_1: No hired manager
4. Bus. Organization (4)	B_2, B_3, B_4	B^1: individual operator
5 Manure Handling (4)	MN^2_1, MN^3_2, MN^4_3	MN^1: Manure not handled
6. Feed Handling Sys. (5)	CF^1, CF^2, CF^3, CF^4	CF_3: grain and supplement fed separately

[a]Number in parentheses is the number of exclusive classes of the variable.

All five regression models were estimated using ordinary least squares and had the following form:

$$\text{Technical efficiency} = b_0 + b_1\ \text{PI} + b_2\ \text{ECS1} + \ldots + b_6\ \text{ECS5} + b_7 M_2 + b_8 B_2 + \ldots + b_{10} B_4 + b_{11} MN_2 + \ldots + b_{13} MN_4 + b_{14} CF_1 + \ldots + b_{17} CF_4 + e$$

Separate analysis was completed for the southeast region sample and the north central region sample. Since the two regions differ substantially in climate, degree of farm specialization, and farm size, a unique production frontier was estimated for each area as the reference for measuring technical efficiency. Particular production practices could be expected to impact differently on technical efficiency in the two regions. For example climate probably influences the use of confinement facilities and may influence the degree of use of environment control facilities. Regional differences in the impact of environment control on technical efficiency cannot be identified without a separate analysis for each region.

The estimated parameters obtained for all five regression models are presented in Table 14 for the north central region and in Table 15 for the southeast region: the models differed only in terms of the dependent technical efficiency variables. Each model contained a common set of explanatory variables.

Table 14. Estimated coefficients for explanatory regression models of technical efficiency: north central region.

Explan. Var.	Dependent Technical Efficiency Variables				
	1. K(y,x)	2. W*(y,x)	3. W(y,x)	4. F(y,x)	5. T.E.(y_i/Y)
Intercept	0.9418	0.9413	0.9607	1.00	0.5577
PI	0.0036	0.0035	0.0029	0.0011	0.0037
	(1.93)[a]	(1.84)	(1.53)	(0.57)	(1.83)
ECS1	-0.0073	-0.0015	-0.0093	-0.0112	0.0478
	(0.20)	(0.04)	(0.25)	(0.28)	(1.19)
ECS2	0.0395	0.0514	0.0454	0.0438	0.0660
	(1.06)	(1.37)	(1.19)	(1.08)	(1.64)
ECS3	0.0616	0.0645	0.0605	0.0462	0.0780
	(1.57)	(1.64)	(1.50)	(1.08)	(1.84)
ECS4	0.0489	0.0465	0.0408	0.0189	0.0915
	(1.05)	(1.00)	(0.86)	(0.37)	(1.82)
ECS5	0.0530	0.0756	0.0700	0.0488	0.1228
	(1.03)	(1.46)	(1.33)	(0.87)	(2.20)
M_2	-0.0263	-0.0199	-0.0245	-0.0035	0.0634
	(0.77)	(0.58)	(0.70)	(0.10)	(0.71)
B_2	-0.0735	-0.0627	-0.0677	-0.0790	0.0435
	(1.45)	(1.23)	(1.31)	(1.43)	(0.79)
B_3	0.1042	0.1153	0.1095	0.0950	0.1034
	(1.41)	(1.55)	(1.44)	(1.18)	(1.29)
B_4	0.0089	-0.0031	-0.0037	-0.0225	0.0020
	(0.14)	(0.05)	(0.06)	(0.32)	(0.30)
MN_2	-0.2232	-0.2224	-0.1989	-0.1753	-0.0229
	(1.90)	(1.88)	(1.65)	(1.37)	(0.18)
MN_3	-0.1956	-0.1805	-0.1724	-0.0496	0.1322
	(1.58)	(1.46)	(1.37)	(1.11)	(0.99)
MN_4	-0.2428	-0.2424	-0.2345	-0.2103	0.0969
	(1.99)	(1.98)	(1.88)	(1.58)	(0.74)
CF_1	0.1910	0.1995	0.1825	0.1390	0.0409
	(2.55)	(2.66)	(2.39)	(1.71)	(0.51)
CF_2	0.0041	0.0070	-0.0044	-0.0268	0.0572
	(0.08)	(0.13)	(0.08)	(0.45)	(0.97)
CF_3	0.0106	0.0296	0.0157	0.0110	0.1085
	(0.19)	(0.52)	(0.27)	(0.18)	(1.76)
CF_4	0.0191	0.0201	0.0177	0.0133	-0.0035
	(0.33)	(0.34)	(0.30)	(0.21)	(0.06)
R^2 - stat.	0.1554	0.1982	0.1632	0.1354	0.5291

[a]t-ratios are in parenthesis.

Table 15. Estimated coefficients for explanatory regression models of technical efficiency: southeast region.

Explan. Var.	Dependent Technical Efficiency Variables				
	1. K(y,x)	2. W*(y,x)	3. W(y,x)	4. F(y,x)	5. T.E.(y_1/Y)
Intercept	0.6830	0.6766	0.7584	0.8202	0.2367
PI	0.0047	0.0053	0.0048	0.0030	0.0067
	(3.12)[a]	(3.39)	(3.06)	(1.85)	(3.75)
ECS1	-0.0034	-0.0021	-0.0166	-0.0155	0.0857
	(0.14)	(0.08)	(0.64)	(0.58)	(2.91)
ECS2	-0.0130	0.0038	-0.0109	0.0044	0.1399
	(0.52)	(0.15)	(0.42)	(0.16)	(4.74)
ECS3	-0.0645	-0.0400	-0.0539	-0.0416	0.0949
	(1.96)	(1.16)	(1.55)	(1.17)	(2.36)
ECS4	0.0298	0.0679	0.0541	0.0912	0.1835
	(0.81)	(1.76)	(1.40)	(2.29)	(4.18)
ECS5	-0.0532	-0.0131	-0.0217	0.0647	0.0914
	(1.18)	(0.28)	(0.46)	(1.32)	(1.70)
M_2	0.0276	0.0498	0.0426	0.0266	0.1356
	(1.11)	(1.90)	(1.62)	(0.99)	(4.51)
B_2	-0.0083	-0.0066	-0.0051	-0.0166	0.0240
	(0.15)	(0.11)	(0.09)	(0.27)	(0.34)
B_4	0.1018	0.0840	0.0722	0.1568	-0.0175
	(1.19)	(0.94)	(0.80)	(1.69)	(0.14)
MN_2	-0.0419	-0.0406	-0.0421	-0.0436	0.0107
	(1.73)	(1.59)	(1.64)	(1.65)	(0.37)
MN_3	0.0078	-0.0008	-010140	-0.0153	0.1141
	(0.34)	(0.04)	(0.58)	(0.62)	(4.18)
MN_4	0.0002	0.0054	-0.0101	-0.0054	0.0965
	(0.01)	(0.19)	(0.35)	(0.18)	(2.97)
CF_1	-0.0242	-0.0084	-0.0486	-0.0707	0.1888
	(0.43)	(0.08)	(0.82)	(1.16)	(2.84)
CF_2	-0.0448	-0.0384	-0.0838	-0.0779	0.1226
	(0.96)	(0.78)	(1.70)	(1.54)	(2.22)
CF_3	-0.0636	-0.0508	-0.0994	-0.0859	0.1882
	(1.30)	(0.99)	(1.92)	(1.61)	(3.23)
CF_4	-0.0098	-0.0056	-0.0282	-0.0304	0.0835
	(0.19)	(0.10)	(0.52)	(0.54)	(1.36)
R^2 - stat.	0.0862	0.0967	0.0993	0.0915	0.4602

[a]t-ratios are in parenthesis.

North Central Region

Model 1. The original "Farrell" technical efficiency measure, K(y,x) was used as the dependent variable in Model 1. Technical efficiency was measured relative to a rather restrictive assumption that frontier technology was characterized by constant returns to scale and strong disposability of inputs. The management factors hypothesized to explain variation in technical efficiency included production intensity, PI, and five classification variables relating to production practices used in hog production.

The estimated coefficient for the production intensity variable, PI, was positive, indicating that an increase in the production intensity of the hog production activity was associated with higher firm technical efficiency. Based on the estimates a one unit increase in the production intensity, interpreted as one more market hog produced per sow per year from the herd, was associated with a gain in enterprise technical efficiency of 0.0036 or 0.36 percentage points. The sign of the coefficient for the variable PI conformed to expectations. However, explanatory power of this variable was not very strong (t = 1.93).

Interpretations of the estimated coefficients of the dummy variables are best discussed in groups. Estimated coefficients in each case showed differences in the intercept value of the estimated function in comparison to the omitted classes. The environment control dummies ECS0 thru ECS5 were exclusive classes of different levels of environment control used in the production system. The five production phases for which environment control was specified were breeding, gestation, farrowing, nursery and finishing. The six variables in this group represent the use of environment control in 0 to 5 phases (ECS0; No Environment Control) through 5 of 5 phases (ECS5; Total Environment Control) of the system. For example, for ECS1 environment control was present in only one of the five phases but it could be either phase. ECS2 included cases where environment control was present in two of the phases; ECS3 indicated environment control was present in three of the phases; ECS4 indicated environment control in four of the five phases; and ECS5 was the category indicating environment control for all five phases. Within each level of environment control the possible combinations were aggregated to enlarge the subsample, but the exclusiveness of each environment control class variable was maintained.

Estimates of the coefficients for the five environment control variables, ECS1--ECS5 can be interpreted as the change in firm technical efficiency rating associated with the level of environment control indicated by the variable name. The omitted class was ECS0--no environment control in either of the phases. A positive affect on technical efficiency was indicated for the variables ECS2, ECS3, ECS4, and ECS5, the higher levels of environment control use. For ECS1, the case where only 1 phase of the production process was under environment control, the estimated coefficient was -0.0073. This estimate indicated that when only one production phase was environmentally controlled, technical efficiency of the enterprise was actually diminished compared to no environment control in either phases. Among the environment control variables, ECS3 had the largest positive influence with a coefficient value of 0.0616. The next largest coefficient for environment control variables was for ECS5 where b = 0.0530. Comparing these estimates indicated that when 3 of 5 phases of the hog production enterprise were under environment controlled conditions, the relative technical efficiency may be even greater than hog farms operating with total environment control level, ECS5. None of the coefficient estimates for variable ECS1 thru ECS5 was significantly different from zero, at the 90% level of confidence. Coefficients for ECS4 and ECS5 were slightly lower than ECS3 but were positive. Based on this model, extending environment control beyond three of the five phases did not appear to improve technical efficiency.

The next explanatory variable hypothesized to be related to enterprise technical efficiency was a management variable. The omitted class of this dummy variable was M_1, the case where no hired management was involved with the hog enterprise. Variable M_2 identified those hog enterprises that did have a hired farm manager. The coefficient estimate for variable M_2 was -0.0263. Since the t-ratio for this estimate, was 0.77, little confidence can be placed on this coefficient. The negative sign for the M_2 coefficient was contrary to the expectation that hired managers have superior management skills, thus contributing to higher resource productivity.

Another variable hypothesized to be related to firm technical efficiency was represented by the dummy variable group B_1, B_2, B_3, and

B_4. Each designated a different type of farm business organization. B_1, (the omitted class) was defined as the case of an individual owner-operator. B_2, B_3 and B_4 were the dummy classes included in the model to indicate partnership, cooperative, or corporate business organizations, respectively. The coefficient estimates for types of business organizations varied considerably; -0.0735 for B_2 (partnership), 0.1042 for B_3 (cooperative),and 0.0089 for variable B_4 (corporate). None of the coefficient estimated for this group were significant at the 90% level. Even so the estimates provide some evidence that partnership organizations were least efficient and cooperative forms were most efficient. The significance level of these two coefficients was about 85%.

Variation in manure handling system used was also hypothesized to be related to farm technical efficiency. Variables MN_2, MN_3, and M_{N4} were used to classify the manure handling system of farms by the form in which the manure was handled. Dry manure handling was designated as MN2. MN_3 designated liquid manure handling. MN4 designated both dry and liquid manure handled. MN1, the omitted class was used to designate cases where manure was not handled. Estimates of the coefficients for the manure handling variables were all quite close in value, -0.2232 for MN_2, -0.1956 for MN_3 and -0.2428 for MN_4. Coefficients were significant at 85% level or greater. The negative coefficients were contrary to expectation, indicating lower technical efficiency for firms with manure handling systems.

The last group of explanatory variables, CF_1, CF_2, CF_3, and CF_4, were used to represent four different types of feed and feed processing methods. The omitted variable class was CF_5, the case where grains and supplements were fed separately. The hypotheses was that technical efficiency of the hog enterprise was influenced by methods of feeding and feed processing. Variable CF_1 designated situations where a completely formulated feed was purchased. Variable CF_2 was used for situations where a complete feed was used, but processing was characterized by portable mill technology. Variable CF_3 indicated the use of complete feeds, but processing was done with a stationary mill. CF_4 indicated the use of complete feeds, but the ingredients were custom milled and formulated on the farms. Estimated coefficients were 0.1910 for variable CF_1, 0.0041 for CF_2, 0.0106 for CF_3 and 0.0191 for CF_4.Since only CF1 was statistically significant above the 50% level little confidence can be placed in the differential impact of this set of variables. The positive sign for these coefficients indicated a positive relationship between enterprise technical efficiency and those feeding practices of using completely formulated feeds when compared to feeding practices of feeding grain and supplements separately. Comparing the different types of farm practice for feed processing described by variables CF_1 thru CF_4, the most notable feature was that the coefficient for variable CF_1 was much larger than on variables CF_2, CF_3, or CF_4. Based on these results the feeding of a purchase completely formulated feed was associated with an improvement in measured technical efficiency by as much as 19 percentage points when compared to the practice of feeding grains and supplements separately.

As a summary of the results for Model 1, it should be noted that only the variables PI, MN_4 and CF_1 had coefficients significantly different from zero at the 95% level, and of these the coefficient on MN_4 was opposite to the expected sign. The sign and relative magnitude of the other coefficient estimates are more or less within expectation, but not statistically significant at the 95% level of confidence. The model, as specified, had little explanatory power for explaining the observed variation in technical efficiency in the north central sample of hog enterprises. The R^2 measure of model fit was 0.16.

Model 2. Specification for model 2 was identical to Model 1 in terms of explanatory variables, but differed in the type of technical efficiency measure used as the dependent variable. As an alter- native to using measured technical efficiency relative to a strict constant returns production frontier, the dependent variable for Model 2 was technical efficiency $W^*(y,x)$ measured relative to a production frontier allowing for constant and/or nonincreasing scale returns. This measure of technical efficiency resulted in a distribution for the sample with less variation and higher mean. This was expected as the frontier specification was less restrictive, resulting in more firms on the frontier and somewhat smaller deviations of other firms from the frontier: the mean of the technical efficiency measure used in Model 2 was 0.7274 compared to 0.6990 for the technical efficiency measure used in Model 1.

The coefficients estimated for Model 2 were nearly identical in terms of magnitude, sign and significance level to those of Model 1. The only exception was the coefficient for B4 which was positive for Model 1 and negative for Model 2. The R^2 measure for Model 2 was slightly higher (0.1982 compared to 0.1554), but both models had rather limited explanatory power.

Model 3, Model 3 included the same explanatory variables but differed from Model 2 in that the dependent technical efficiency variable was generated by a still less restrictive frontier. For Model 3 technical efficiency W(y,x) was measured relative to a production frontier which allowed variable scale returns. Estimated coefficients were very similar to those of Model 2 in terms of the magnitude, sign and statistical significance. The R^2 statistic was 0.1632, slightly lower for Model 2 and slightly higher than for Model 1.

Model 4, The independent variable used for Model 4 were identical to those used for Models 1, 2, and 3. The technical efficiency measure F(y,x) of Model 4 was based on an assumed variable returns to scale frontier, as was the case for W(y,x) used in model 3. The difference between W(y,x) and F(y,x) was that F(y,x) was an estimate of technical efficiency relative to a variable scale returns frontier assuming weak disposability of input instead of strong disposability of input as was the case for W(y,x). For Model 4 the same independent variables were used as in Models 1, 2, 3.

Estimated coefficients for each of the variables in Model 4 were, almost without exception, smaller than obtained in Models 1, 2, and 3 but had the same sign. The coefficient for PI was 0.0011, indicating a positive relationship between technical efficiency and production intensity but only 1/3 of the magnitude estimated for Model 1, 2, and 3. The coefficient on variable ECS1 was negative as for Models 1, 2,and 3. but the absolute value was much larger. The coefficient estimates for the other environment control variables were positive but generally smaller than the estimates for ECS2, ECS3, ECS4 and ECS5 of the first three models. The relative ranking of the influence of each level of environment control on firm technical efficiency was consistent with the results of the previous Models, ECS5 > ECS3 and ECS2 > ECS4. The standard errors of estimates for these coefficients remained large. The coefficient estimates on ECS2, ECS3, ECS4, and ECS5 have t-ratios reflecting even a lower probability of being statistically different from zero compared to the first three models. The coefficient estimate for M_2 was -0.0035, smaller than the value estimated for Models 1, 2, and 3.

The estimated coefficients for B_2 and B_3 were -0.0790 and 0.0950 respectively, nearly unchanged in value and significance compared to the results of Models 2 and 3. The coefficient estimate for B_4 (corporate organization), while still not significant, was a larger negative value indicating even a greater negative relationship with firm technical efficiency, F(y,x) than for Models 2 and 3.

Estimated coefficients on the dummy variables MN_2, MN_3, and MN_4, describing the type of manure handling system used were negative relationships as for Models 1, 2, and 3. The coefficient estimates of MN_2 and MN_4 are slightly lower than in the other three models. The coefficient obtained for MN3, while negative, was much lower than for MN2 and MN4, thus lending some evidence to the notion that liquid manure system may be relatively more efficient than dry manure system.

Coefficients estimated for the dummy variables CF_1, CF_2, CF_3 and CF_4, describing the type of feed and feed processing methods used, were similar to the results obtained for Model 3 except the coefficients were generally smaller. The largest positive coefficient obtained was for CF1 , using completely formulated purchased feed. Estimated coefficients for CF_4 (custom formulated feeds) and CF_3 (complete feeds processed with stationary mill technology) were also positive but very small. The coefficient for CF_2 (complete feeds processed with portable mill technology) had a negative coefficient as was the case for Model 3.

With respect to Model 4 it should be noted that nearly every explanatory variable contributed less to the explanation for the variation in the dependent technical efficiency variable F(y,x) than was the case for the same variable in Models 1, 2, and 3. In most cases the estimated parameter value was smaller and significance level were lower. It should be noted that the mean technical efficiency was higher and the variability of technical efficiency was lower for the

Model 4 estimates than for Models 1, 2, and 3. The R^2 statistic for Model 4 was 0.1354, lower than for either Model 1, 2, or 3.

Model 5. Model 5 included the same explanatory variables as Models 1 through 4. However for Model 5, technical efficiency (TE), the dependent variable was measured in a quite different manner. In this case the frontier production function was a parametric specification that included a composed error term to identify both the random stochastic disturbances, and also the one-sided variation due to firm technical inefficiency. The frontier production function was allowed to vary randomly from firm to firm in accordance with the normally distributed random error component of the error term, thereby identifying a truly stochastic production frontier. A measure of relative technical efficiency was obtained for each firm by expressing TE_{ce} as a ratio of actual output to the expected output on the stochastic production frontier. Measurement of firm technical efficiency in this manner was designed to exclude a firm's displacement from the frontier due to random events outside the farm manager's control. Unlike the deterministic linear programming frontier approach the stochastic composed error frontier approach was designed to adjust for the possibility of error in variable measurement and other random disturbances to the firm that might affect observed production performance. The Cobb-Douglas functional form used for the stochastic frontier estimation can show only homogenous scale returns and strong disposability of input in the frontier production relationship.

Estimated parameters for Model 5 for the north central region are shown in Table 14, p. 89. The estimated coefficient for PI was 0.0037. This was consistent with expectations, i.e., that technical efficiency would improve with increases in the intensity of production (more hogs marketed per sow per year). The coefficient value 0.0037 was interpreted as the expected relative improvement in enterprise technical efficiency as the production intensity of the herd, PI, changes by one, which meant an average of one market hog per sow in the herd. The t-ratio indicated that this coefficient was statistically significant above the 90% level of confidence.

The estimated coefficients for the environment control dummy variables ECS1 thru ECS5 were all positive. The relative advantage in technical efficiency for those hog enterprises using the different levels of environment control as compared to those using none were estimated to be 0.0478 for ECS1, 0.0660 for ECS2, 0.0780 for ECS3, 0.0915 for ECS4, and 0.1228 for ECS5. These positive coefficients conform to the conventional understanding about the positive impact of environment control on hog production. Their relative ranking by coefficient value indicated that in this sample, each increase in intensity of environment control resulted in improvement in enterprise technical efficiency. Coefficient for ECS2, ECS3, ECS4, and ECS5 were all significant at the 90% level or better.

The estimated coefficient for M2 was 0.0634. This estimate can be interpreted to mean firms using a hired manager, were 6.3 percentage points more technically efficient than those operated by a hired manager. This result was not unreasonable as the presumed superior skills of a hired manager may be able to extract a higher productivity from the resources employed in hog production. The t-ratio for this estimate was 1.71, indicating a significance level of above 90%.

The type of business organization was represented by variable B_2, B_3, and B_4. Estimated coefficients in each case were positive indicating that compared to an individual owner-operator type of farm business, partnerships (B_2), cooperatives (B_3), and corporations (B_4) were more technically efficient. The coefficient for the cooperative organization (B_3), was greatest with a value of 0.1034, followed by the corporate business organizations (B_4), with a value of 0.0969, and lastly by the partnership farm organizations with a coefficient value of 0.0435. Thus the cooperative business organization tended to have higher technical efficiency compared to the partnerships or corporations. The coefficient for B3 was significant at about the 80% level. Significance levels for B1 and B3 were quite low, indicating a rather low probability that technical efficiency was greater for partnerships and corporations than for owner-operators.

The variables MN_2, MN_3, and MN_4 were classifications designating the type of manure handling system used. The classification omitted for estimation purposes was MN_1, the case where manure wastes were not handled at all. The estimated coefficient were -0.0229 for MN2 (manure handled in dry solid form), 0.1322 for MN3 (manure handled in liquid form), and 0.0969 for MN4. Handling manure wastes in liquid form appeared to be a more efficient practice compared to handling manure in dry, or dry and liquid forms or not handling wastes at all. The t-ratios indicate a very low level of significance of the coefficients for MN2, MN3, and MN4. Thus for Model 5, type of manure system was not a very meaningful explanatory variable for differences in technical efficiency.

The dummy variables CF_1, CF_2, CF_3, and CF_4 specified the four types of feed and feed processing practices hypothesized to explain variation in technical efficiency among firms. The variable CF_5 (grains and supplements fed separately) was the omitted dummy variable class. Estimated coefficients for variables CF_1, CF_2, and CF_3 were positive but only the coefficient on CF3 was statistically significant at any meaningful level. The estimated coefficient for CF4 was negative and was meaningless because of the low t-ratio. The estimated coefficient for CF3 was 0.1085 indicating that farms that feed complete feeds processed with electric mill technology have a technical efficiency 10 percentage points higher than farms feeding whole grains and supplements separately. The CF3 coefficient was significant at the 90% level of confidence.

For Model 5 estimated coefficients for both continuous and dummy variables were generally according to expectations but level of significance tended to be quite low for many of the variable indicating wide variability of technical efficiency within a variable classification. Only one estimated coefficient, ECS5, had a t-ratio greater than 2.0. Several of the variables had estimated coefficient with t-ratios greater than 1.5; PI, ECS2, ECS3, ECS4, ECS5, and CF_3. The R2 statistic for model 5 was 0.5291, considerably higher than for Models 1, 2, 3, and 4, but indicating the likelihood of other important explanatory variables not included in the models.

Southeast Region

Since the farrow to finish farms of the southeast region were considered to be a separate sample for this study, each of the five technical efficiency measurements, K(y,x), W*(y,x), W(y,x), F(y,x) and TE_{ce} were estimated for each of the 339 observation in the sample. Each technical efficiency measure was specified as the dependent variable of an explanatory model. The same set of independent variables used for the north central region were hypothesized to explain the variation in the dependent technical efficiency variable in each of the five explanatory models. The estimated coefficients for the five regression models applied to the southeast sample of hog enterprises are presented in Table 15, p. 90.

Model 1. The original Farrell measure of technical efficiency, K(y,x),was used as the dependent variable in Model 1. In this case technical efficiency was estimated using linear programming procedures with constraints on the reference frontier to exhibit constant scale returns and strong input disposability. The independent variables included the enterprise production intensity PI, as a continuous variable, and five groups of dummy classification variables identifying production practices used in hog production (see Table 13, p. 87).

The coefficient estimate for the production intensity variable PI was 0.0047. This estimate was consistent with the expectation that a higher production intensity results in greater relative technical efficiency. Based on this estimate each extra hog marketed per sow in the herd would result in an increase in technical efficiency of 0.47 percentage points. This coefficient estimate had a t-ratio of 3.12, indicating significance at the 99% confidence level.

Interpretations of the coefficient estimates for the dummy variables are best discussed by groups. The estimated coefficient for each dummy variable showed the differences in the intercept value of the estimated function in comparison to the omitted class of each variable group. The environment control dummy variables ECS0 thru ECS5 were exclusive classes of different levels of environment control use in the hog production system. The six variables in this group indicated the use of environment control in 0 of 5 phases (ECS0: no environment control) through 5 of 5 phases (ECS5: total environment control) of the production system. The variable ECS0 was omitted for model estimation.

Estimates of the coefficients of the variables ECS1 thru ECS5 can be interpreted as the change in technical efficiency associated with the level of environment control indicated by the variable name, compared to the omitted level of no environment control use. Negative coefficient estimates were obtained for the environment control classes ECS1, ECS2, ECS3, and ECS5 indicating a lower technical efficiency for enterprises using these levels of environment control compared to using none at all. This result was contrary to expectations because the use of environment control facilities has been generally thought to improve the pig environment and the resulting growth and performance of the pigs. ECS3 had the largest negative value of -0.0645. This coefficient estimate was significant at the 95% confidence level. The coefficient estimated for the environment control variable ECS4 was positive (0.0298) but was not significant at any reasonably acceptable level.

The next explanatory variable hypothesized to be related to hog enterprise technical efficiency was a management variable M_2. Variable M_2 identified those hog enterprises operated by a hired manager. M1, the omitted class for estimation purposes, indicated farms where no hired management was used. The estimated coefficient for variable M_2 was 0.0276. The positive sign for this coefficient was as expected. Hired managers are generally considered to have specialized management skills and thus able to achieve a higher productivity from the resources employed. Since the t-ratio for the M_2 coefficient estimate was 1.11 little confidence can be placed on this result.

Another practice included as an explanatory variable in the model was the type of farm business organization. Each dummy variable, B_1, B_2, B_3 and B_4 characterized a different type of farm business organization. B_1, the variable class omitted from the estimating equation indicated the case of the individual owner-operator farm. Variables B_2 and B_4 were the classes included to represent partnerships and corporate farm business organizations respectively. Variable B_3, the variable representing cooperative organization, was not observed in the southeast sample of hog enterprises. The coefficient estimate for variable B_2, partnership, was -0.0083. This estimate indicated that partnership hog enterprises were slightly less technically efficient compared to individual owner-operator types; however since the t-ratio for this estimate was 0.15 little confidence can be placed on its value. The coefficient estimate on variable B_4 (corporate), was 0.1018, indicating a higher efficiency for corporate organizations. This coefficient was significant at the 85% confidence level.

Variation in the type of manure handling systems used on hog enterprises was hypothesized to be related to sample variation in enterprise technical efficiency. Variables MN_2, MN_3 and MN_4 represented the different forms of handling manure wastes. MN_2 designated the handling of wastes in dry form. MN_3 indicated the handling of manure in liquid form. MN_4 was the classification of firms which handled manure in both dry and liquid forms. The omitted class was MN_1, where manure wastes were not handled. The estimated coefficient for MN_2 was -0.0419, with a t-ratio of 1.73. This value, significant at the 95% confidence level, was interpreted to mean lower technical efficiency with a dry manure handling system as compared to enterprises that do not handle the manure wastes. The coefficient estimates on variables MN_3 and MN_4 were positive, interpreted to mean an improved technical efficiency associated with a liquid or a mix, liquid and dry, manure handling system. However both coefficients had very low t-ratios and little or no confidence can be placed in this relationship.

The last group of explanatory variables were the dummy variables CF_1, CF_2, CF_3 and CF_4, that represented four different types of feed and feed processing methods used in hog enterprises. The omitted variable class was CF_5, the case where grains and supplements were fed separately. The estimated coefficients on all the feed processing variables had negative signs. This result was contrary to expectations. Since the variables CF_1, CF_2, CF_3 and CF_4 all involved the use of completely formulated feeds it was expected that these coefficients would have a positive sign. The use of completely formulated feed is considered to be a best management practice and to result in improved pig growth and performance. Only the coefficient estimate on variable CF_3, complete feeds processed with stationary mill technology, can be considered significantly different from zero with a 90% confidence.

For Model 1 only the coefficient estimates for the variables PI, ECS3, and MN_2 could be considered significantly different from zero at the 95% level of confidence. The negative coefficient obtained for ECS3 was contrary to expectations. The signs of the coefficients on PI and MN_2 were according to expectations. The model as a whole however showed very little explanatory power for the variation in the dependent technical efficiency variable K(y,x). The R^2 statistic for the estimation was 0.0862.

<u>Model 2</u>. Model 2 was identical to Model 1 in terms of independent variables, but differed in the type of technical efficiency measure used as the dependent variable. The measure

of technical efficiency for model 2 was W*(y,x), which was measured relative to a production frontier which allowed constant and/or nonincreasing scale returns. The mean value for the dependent variable W*(y,x) was higher than the mean value for the K(y,x). This was expected since the less restrictive modeling of W*(y,x) allowed more hog enterprises to be on the frontier. The regression results obtained for Model 2 were similar to those obtained for Model 1. The estimated coefficient for PI in Model 2 was 0.0053 with a t-ratio of 3.39, both very similar to the Model 1 result. Similar results were also obtained for the coefficient estimates on the dummy variables, in terms of magnitude, sign, and significance levels. The R^2 statistic for Model 2 was 0.0967 only slightly higher than for Model 1.

Model 3. Model 3 had the same independent variables and differed from Models 1 and 2 only in the type of dependent technical efficiency variable. The technical efficiency variable for model 3 was W(y,x), measured relative to a production frontier model which allowed fully variable scale returns in the cross sectional frontier. This type of frontier reference resulted in a higher mean technical efficiency for the sample. Estimated coefficients were quite similar to those obtained for Models 1 and 2 despite the differences in the technical efficiency measure used in the model and the smaller variation in technical efficiency. The estimate for PI of 0.0048 was highly significant as it was in previous models. Variables with estimated coefficients with t-ratios at or near acceptable levels of significance in Models 1 and

2, were likewise significant for Model 3. The estimated R2 was 0.0993, about the same as for Model 1 and Model 2.

Model 4. The dependent variable F(y,x) in Model 4 like W(y,x) of Model 3 was a measure of technical efficiency referenced by a variable scale returns frontier, but unlike W(y,x), the variable F(y,x) was calculated assuming the frontier exhibits weak input disposability. This assumption about the frontier permits a firm to be perfectly efficient even if there exists some stage III production with some inputs commonly called congestion. This type of frontier model allowed more firms to be on the frontier and also resulted in a higher mean technical efficiency for the sample compared to the first three measures.

The estimated coefficients for the independent variables in Model 4 were largely the same in magnitude, sign, and significance level as were the estimates for the previous models. The estimated coefficient for PI was 0.0030 with a t-ratio of 1.85. The estimates on the environment control variables ECS4 and ECS5 had positive values and were significant at better than the 90% confidence level. Surprisingly the environment control level ECS3 was estimated to have a negative impact on technical efficiency. The reasonable expectation was for all environmental control variables to have positive signs.

The estimated coefficient for M_2 in Model 4 was 0.0266 with a t-ratio of 0.99. This estimate conformed to prior expectations but the t-ratio was too low to attach much significance to this result.

The relationship between firm technical efficiency and type of farm business organization was estimated to be negative for the partnership organization and positive for the corporate organization. The estimate for B_2 (partnership) was -0.0166 and was non significant. The estimate for B_4 (corporate) was 0.1568 and was significant at the 99% confidence level. This strong association for the corporate farm organization was not encountered in other models.

Estimated coefficients for MN2, MN_3 and MN_4 were all negative, indicating a negative relationship between manure handling system and technical efficiency. The estimated coefficient for MN2 was -0.0436, similar to results obtained for the other models. Negative coefficients for MN_3 and MN_4 were surprising and certainly counter to the notion that removing wastes will improve the pig's environment and performance.

The estimated coefficients on the variables CF_1, CF_2, CF_3 and CF_4 were all negative, indicating lower technical efficiency for the various completely formulated feeding systems than for the reference variable CF5, were grains and supplements were fed separately. Coefficients for CF2 and CF3 were statistically significant at the 90% confidence level. But, as indicated earlier, the results obtained for these variables were contrary to expectations.

The R2 estimates for Model 4, was 0.0915, attesting to the very limited explanatory power of the model. None of the Models 1 thru 4 can be considered as satisfactory for explaining variation in technical efficiency among firms. Many of the coefficients were opposite in sign to the expected relationship and for most significance levels of the coefficients were below commonly accepted standards. While some differences exist, coefficients for particular variables were similar for the four models. In each case the model explained less than 10% of the variation in the dependent variable.

Model 5. The explanatory variables used for Model 5 were the same as used for Models 1 thru 4. The dependent variable, however, was estimated in a quite different manner. For Model 5 the dependent variable was a measure of enterprise technical efficiency true to the Farrell notion that the phenomenon of inefficiency is a one-sided event relative to some identified frontier, but the technical efficiency measure (TE_{ce}), was obtained by a statistical approach. TE_{ce} was obtained by estimating a parametric production function with a composed error disturbance structure. One component of the error term was used to identify the stochastic production frontier. The other error term component was assumed to have a one-sided distribution from which an estimate of inefficiency for each observation was obtained. The stochastic frontier approach that uses composed error modeling was specifically designed to contend with the possibility of random error disturbances on the sample observations and to disassociate these errors from the observation's frontier displacement reflecting technical inefficiency.

The estimated coefficients for Model 5 for the southeast region are shown in Table 15, p. 90. The estimated coefficient for PI was 0.0067. This estimate was consistent with the expectation that hog enterprises operating at a higher production intensity were likely to be more technically efficient. The coefficient value indicated that obtaining one more market hog per sow per year would improve technical efficiency by 0.67 percentage points. This coefficient had a t-ratio of 3.75, considered highly significant.

The estimated coefficients for the environment control dummy variables were all positive and statistically significant at the 95% confidence level. The positive signs were consistent with the expected influence of the various levels of environment on hog production performance, compared to the using no environment control (ECS0). A ranking of the relative impact of different levels of environment control on technical efficiency can be made by comparing the six coefficients. The estimated coefficients were 0.1835 for ECS4, 0.1399 for ECS2, 0.0949 for ECS3, 0.0914 for ECS5 and 0.0857 for ECS1.

The estimated coefficient for the the management variable (M_2) was 0.1356. This can be interpreted to mean that hog firms with hired management were more technically efficient. The mean level of those with hired management would be 13.5 percentage points higher than those with no hired manager. The t-ratio for this coefficient was 4.51, significant above the 99% level of confidence. The positive sign for M_2 was consistent with the expectation that hired managers have specialized management skills and thus likely to achieve a higher productivity from the resources employed.

The estimated coefficient for the business organization dummy variables B_2 and B_4 were 0.0240 and -0.0175 respectively. Variable B_2

(partnership) had a positive coefficient and was interpreted to mean a greater technical efficiency of partnership as hog enterprises compared to individual owner-operator hog enterprises. Variable B_4 (corporate) had a negative coefficient indicating a lower technical efficiency for this type of organization. Since the t-ratios were 0.34 and 0.14 for B_2 and B_4 respectively, statistical significance levels were too low to attach much meaning to these relationships.

The estimated coefficient on the manure system dummy variables MN_2, MN_3 and MN_4 were all positive. The estimates were 0.0107 for variable MN_2, 0.1141 for variable MN_3, and 0.0965 for variable MN_4. The estimates for MN_3 and MN_4 were statistically significant at the 99% confidence level. The confidence level for the estimated coefficient for MN_2 was very low. The estimate on variable MN_3, liquid manure system, had the largest coefficient followed by variable MN_4, dry and liquid manure system, and then lastly by variable MN_2, the dry manure system. It was expected that the liquid manure system that quickly removes manure from the pig environment (slatted floors and flush gutter designs) would show the strongest positive relationship with firm technical efficiency.

The variables CF_1, CF_2, CF_3 and CF_4 classified the firms into groups on the basis of the feeding of completely formulated rations processed by various techniques. The omitted variable CF_5 represented the case where grains and supplements were fed separately. The estimated coefficient for variable CF_1, feeding purchase complete feeds, was 0.1888 and was statistically significant at the 99%

confidence level. The next largest coefficient was 0.1882 for CF_3 the practice of feeding a complete feed processed with on farm stationary mill technology. This coefficient was also significant at the 0.01 level. CF_2 representing the practice of feeding a complete feed processed with portable mill technology, and had an estimated coefficient of 0.1226, significantly different from zero at a 95% confidence level. Variable CF_4, representing the practice of feeding a complete feed that was custom processed on the farm, had an estimated coefficient of 0.0835 which was significant at the 90% confidence level. All the estimated coefficients for this class of variables had the expected sign and collectively were indicative of the greater technical efficiency for feeding completely formulated feeds as compared to feeding grains and supplements separately.

Overall the results obtained for Model 5 were quite satisfactory. Estimated coefficients generally had the expected sign and relationships to other variables. Thirteen of the sixteen estimated coefficients were significant at the 90% confidence level or better. The R2 estimate for model 5 was 0.4602, much greater than for Model 1 thru Model 4.

CHAPTER V

SUMMARY AND CONCLUSIONS

The study of economics is in many ways the study of efficiency. The decision rules assumed in most economic models require agents to pursue some type of optimization. Optimum is efficient relative to some prescribed criteria. Allocative efficiency, one type of efficiency of concern, is the type most easily observed in the market place. Other types of efficiency may be even more important in determining economic efficiency of the use of scarce resources. Of particular concern in this study was technical or productive efficiency, generally defined as the extent to which the greatest possible output is achieved from any given set of inputs. Technical efficiency is an activity completely internal to the firm, generally considered an important management problem, but often not a primary focus in economic studies of firm behavior. Recent interest by economists in technical efficiency has been fostered by the growing recognition that technical efficiency can be measured by a variety of production frontier estimation techniques developed primarily by Farrell, Bressler, and Aigner and Chu, and that firm growth is closely related to the factors that bring a firm to use "best" practices rather than "average" practices. The delineations between best and average is in part a matter of technical efficiency, a distinction impacting the firm's competitiveness and viability.

The inclusion of technical efficiency into economics has been largely ad hoc with few attempts to place the concept in the context of economic theory. In this study five measures of technical efficiency were estimated that were considered to be consistent with various assumptions about technical conditions facing farrow to finish hog production firms in the north central and southeast regions of the United States. Statistical models were developed and estimated to relate specific production practices to variation in technical efficiency among firms as estimated in phase 1.

Summary

The data used for this study were derived from the U.S.D.A. 1980 Cost of Production of Hogs Survey, conducted in 1981. Observations obtained for 216 farrow to finish hog enterprises in the north central region constituted the north central sample. Observations obtained for 339 farrow to finish hog enterprises in the southeast region constituted the southeast sample. These data obtained by personal interview, provided the primary input-output measurements that were used both for frontier function estimates of technical efficiency, and for identifying production practices hypothesized to explain variation in technical efficiency among firms. The frontier production function included a single output measure, hundred weight of hogs marketed annually, and four independent variables; labor, feed, capital and miscellaneous input expenditures.

Two different frontier function approaches presented in Chapter 3 were used and five different technical efficiency estimates were made for each observation in each sample. The first approach was a deterministic model for measuring enterprise technical efficiency and was obtained as solutions to linear programming problems. The first four technical efficiency measures, K(y,x), W*(y,x), W(y,x) and F(y,x) were the results of measuring the output shortfall of the enterprise relative to some frontier level of production. The frontiers for these measures were identified through the linear program modeling and the four measures were the result of four variations in underlying assumptions about the technical conditions facing the firm. The frontier reference for K(y,x) was a constant returns to scale frontier. The frontier reference for W*(y,x) was a nonincreasing returns (constant and/or decreasing) to scale frontier. The frontier reference for W(y,x) was a fully variable returns to scale frontier. The frontier reference for F(y,x) allowed not only variable returns to scale but also weak input disposability called congestion, or stage III production.

Mean technical efficiency for hog producers in both regions was higher as the frontier function was made less and less restrictive. For the north central sample ,the mean K(y,x) was 0.8077,the mean W*(y,x) was 0.8205, the mean W(y,x) was 0.8308 and the mean F(y,x) was 0.8517. For the southeast sample,the mean K(y,x) was 0.6990,the mean W*(y,x) was 0.7274,the mean W(y,x) was 0.7428 and the mean F(y,x) was 0.7887. Using these four estimates it was possible to decompose the original

Farrell measure K(y,x) into its pure technical efficiency (F(y,x)), scale efficiency (S(y,x)) and congestion efficiency (C(y,x)) components. The relationship between these various measures is as follows; $K(y,x) = F(y,x) \cdot S(y,x) \cdot C(y,x)$. Each component of efficiency was computed for each firm. Results of this analysis indicated that neither scale nor congestion inefficiency was a prominent factor in the above relationship. For the north central sample,the mean S(y,x) was 0.9732 and the mean C(y,x) was 0.9976 while the mean pure technical efficiency F(y,x) was 0.8517. For the southeast sample,the mean S(y,x) was 0.9437 and the mean C(y,x) was 0.9456 while the mean pure technical efficiency F(y,x) was 0.7887.

Using the mean observed output of the north central sample as a point of reference, the output shortfall (inefficiency) of the observed mean output relative to the CRS-SDI frontier output was 1041 hundredweight of market hogs. The proportional share of this output shortfall was 83% for pure technical inefficiency, 15% for scale inefficiency and 2% for congestion inefficiency. Using the mean observed output for the southeast sample as a point of reference, the indicated output shortfall of the mean observed output relative to the CRS-SDI frontier was 1925 hundredweight of market hogs. The proportional shares of this shortfall attributable to pure technical inefficiency, scale inefficiency, and congestion inefficiency, was 64%, 19% and 17% respectively. When scale inefficiency was indicated, the unrestricted VRS frontier K(y,x) deviated to some degree from constant returns to scale technology. For both regional samples, results as to the type and frequency of scale inefficiency in each cross section indicated the VRS (Variable Returns to Scale) frontier exhibited predominantly IRS (Increasing Returns to Scale) in the lower output categories, but predominantly DRS (Decreasing Returns to Scale) technology in the higher output categories.

The alternative frontier approach to measuring enterprise level technical efficiency and applied to both regional cross-sectional samples was a statistical estimation of a parametric model using a composed error structure to identify the production frontier and thus provide a basis for estimating technical efficiency. A Cobb-Douglas functional form was used for the frontier estimation. For each sample, coefficient of the stochastic production function were positive for each of the input variables and the elasticity of production was less than one for each factor and for all factors collectively. For each regional stochastic frontier model the proportion of the total variation in hog output explained by the input variables included in the regression model was greater than 94%.

Composed error modeling of the production frontier allowed estimation of the variance parameters of the two error components. Estimates of the total error variance, σ^2, and the estimate of lambda, λ (a ratio of the two error component variances), made it possible to specify the normally distributed error component to represent the random variation of a "stochastic" production frontier function. The remaining one-sided error component distribution was then used to depict the one-sided frontier displacement interpreted as technical inefficiency. Point estimates from the conditional distribution of the one-sided error term of the model provided the estimates of the distance, in output terms, each observation was from the stochastic frontier.

For the north central sample, estimations from the composed error model indicated that the normally distributed error component was much larger than the one-sided error distribution. This implied that when normal stochastic variation in firm to firm output was accounted for, very little firm to firm variation due to technical inefficiency remained. For the southeast sample, the results of the composed error model estimation showed the reverse situation, i.e., the error variance component embodying technical inefficiency was much larger than the normal stochastic error variance component. This meant that most of the total error variance can be attributed to the firm to firm variation in technical inefficiency. The mean of the technical efficiency estimates for the north central sample of hog enterprises was 0.7832. The mean of technical efficiency estimates for the southeast sample was 0.6203.

Both frontier approaches, the linear programming approach and the stochastic compose error modeling approach, provided estimates of technical efficiency on an observation by observation basis. The resulting estimates of technical efficiency differed first by the type of reference frontier, i.e., K(y,x), W*(y,x), W(y,x) and F(y,x) and secondly by statistical foundation, i.e., TE_{ce}. It should be noted however that sample mean technical efficiency obtained from the determinist models , K(y,x) was .8077 for the north central region and .6990 for the southeast region. These estimates were very similar to the mean stochastic frontier technical efficiency estimates of .7832 for the north central and .6203 for the southeast.

The five technical efficiency measures obtained for each observation were used as five different dependent efficiency variables in explanatory regression models developed for each of the two regions. The objective addressed by these statistical models was to determine the effect of specified hog production practices on technical efficiency. Separate explanatory statistical models were developed for each of the technical efficiency measures. The specified explanatory independent variables included one continuous variable, production intensity, and five groups of dummy variables which classified firms based on use or nonuse of particular production practices. The production practices postulated as explanatory variables included level of environment control, type of hired management type of business organization, type of manure handling practices, and type of feed and feed processing practices.

The estimated coefficients for explanatory variable in Models 1 thru 4 that had deterministic dependent technical efficiency estimated were largely the same sign, magnitude and statistical significance for each model. This result was not totally unexpected since the dependent technical efficiency variables used in Models 1 thru 4 were similar in many respects and were obtained by the same linear programming method. Estimated coefficients obtained for each of the explanatory variables were quite different for Model 5 as compared to Models 1 thru 4. The technical efficiency measurement used for Model 5 was a statistical measure.

Production Intensity of the Sow Herd

Results obtained for all five models in each region indicated a positive effect on technical efficiency of increasing the production intensity of the sow herd. For Models 1, 2, 3 and 5 of the north central sample, the estimated coefficients for the production intensity variables were significant with at least an 80% confidence and in the models of the southeast, with better than a 90% confidence.

Level of Use of Environment Control

Coefficients obtained for the environment control variables, ECS1 thru ECS5, were generally positive in each of the five models estimated for the north central sample. This was consistent with generally held expectations for a positive effect from use of environment control practices. For Models 1 thru 4 only the estimated coefficient on variable ECS3 was significantly different from zero at the 75% confidence level or higher. For Model 5, coefficients obtained for each of the environmental control variables were significant at the 75% confidence level or better.

For the southeast sample, the estimated coefficients obtained for the environment control variables were considerably different for Model 5 as compared to Models 1 through 4. For Models 1 through 4 estimates indicated a positive effect on technical efficiency for some levels of use of environment control compared to nonuse, and a negative effect for other levels of use. The expected or hypothesized effect was for a positive relationship for all levels of environment control. For Model 5 results for the southeast sample estimated coefficients for the environment control variables were all positive as expected and each coefficient was significant at the 90% confidence level or higher.

Hired Management

For Models 1 through 4 of the north central sample estimates indicated a negative effect of hired management on technical efficiency but estimates were not significant at commonly accepted confidence levels. Estimates obtained for Model 5 of the north central sample indicated a positive effect of hired management on firm technical efficiency and the estimate was significant with an 80% confidence.

For the southeast region estimates obtained for all five models indicated a positive effect of hired management on technical efficiency, which was the prior expectation. Confidence levels for estimates obtained in Models 1 through 4 were quite low while the estimate for Model 5 was highly significant with a t-value of 4.51.

Type of Farm Business Organization

Types of farm business organization estimated for the north central region, coefficients obtained for partnerships were negative indicating lower technical efficiency for this type of organization than for the omitted class of owner-operators. The estimated coefficients for cooperative were positive indicating a higher technical efficiency for this type of organization than for the omitted class. Estimates obtained for partnerships and cooperatives were significant at the 80% level of confidence or higher. The estimated coefficient for corporations indicated lower technical efficiency than for the omitted class but the estimate was nonsignificant. For Model 5 estimated coefficients for these business organization variables indicated a higher efficiency compared to the omitted class, but only the estimates for the coefficient on cooperatives was significant with 80% confidence.

In the southeast sample, only owner-operator, partnership and the corporate organization types were observed. For Models 1 through 4 estimated coefficients indicated lower technical efficiency for the partnership organization and a higher efficiency for the corporate organization as compared to owner-operator units. Neither of these estimates were significant at the 80% level. Estimated coefficients for Model 5 showed a higher efficiency for the partnership organization and a lower efficiency for the corporate organization compared to owner-operator firms.

Manure Handling Practices

For the north central region estimates obtained from Models 1 through 4 indicated lower technical efficiency for each type of manure handling practice compared to the practice of not handling wastes. The manure handling variables included dry manure handling, liquid manure handling, and both dry and liquid manure handling. Results obtained were contrary to the expected sign. Estimate were significant at the

80% confidence level or higher. For Model 5 estimates generally indicated a positive effect of manure handling systems on technical efficiency but coefficients were not statistically significant.

For the southeast region results obtained for Models 1 through 4 indicated a predominantly negative effect on firm technical efficiency of the various manure handling practices. Only the estimates for dry manure handling were significant with an acceptable level of confidence. Estimated coefficients for manure handling variables in Model 5 of the southeast region however, were all positive indicating that the manure handling practices resulted in higher technical efficiency compared to not handling wastes. for Model 5, coefficients obtained for liquid manure handling practices and both dry and liquid manure practices obtained were highly significant.

Type of Feed and Feed Processing Practices

Results obtained from the five separate explanatory statistical models used for the north central region indicated that, in most instances, each type of feed and feed processing practice had a positive effect on firm technical efficiency compared to the omitted feed practice of feeding grain and supplement separately. In Models 1 through 4 only the estimated coefficients for feeding a purchased complete feed were significant with at least an 80% confidence. Estimated coefficients in Model 5 also indicated the expected positive effect on firm technical efficiency of these variables but only the coefficient for complete feed processed with stationary mill technology was significant at the 80% level.

For the southeast region estimates obtained for Models 1 through 4 indicated the highest technical efficiency for the practice of feeding grain and supplement separate. For Model 5, estimates indicated that technical efficiency was greatest for the situations where a completely formulated feed was used. Results obtained for models 1 through 4 were inconsistent to prior expectations. For Models 1 through 4, most of the coefficients were not statistically significant. The estimated coefficients for the feeding practice variables in Model 5 of the southeast sample indicated a positive effect on technical efficiency compared to the practice of feeding grains and supplements separately. The estimates obtained for three of the variables were highly significant at the 95% confidence level while the estimate on an additional variable was significant at the 80% confidence level.

In both regional samples, the estimation of Models 1 thru 4 depict the poor explanatory power of the specified explanatory variables both individually and collectively. The R^2 measures of model fit for Models 1 thru 4 of the north central sample indicated that less than 20% of the total variation in firm technical efficiency was explained. In the southeast sample, the explanatory variables of Models 1 through 4 explained less than 10% of the variation in firm technical efficiency. The R^2 measures for Model 5 for each region indicated a greater explanatory power of the explanatory variables when dependent measures of firm technical efficiency were estimated by a statistical frontier estimation procedure. The R^2 statistics for Model 5 was .5291 for the north central region and .4602 for Model 5 for the southeast region.

Conclusion

Alternative frontier function methods of estimating firm technical efficiency were applied to regional samples of farrow-to-finish hog production units. Measures of technical efficiency were obtained for each of 216 farrow-to-finish hog units in the north central sample and each of the 339 farrow-to-finish hog units of the southeast sample. Initially, firm technical efficiency of each observation was estimated with a deterministic frontier method using linear programming procedures. The linear programming approach gave estimates of "Farrell" technical efficiency and allowed the decomposition of this overall technical efficiency into the components of scale inefficiency, congestion inefficiency, and pure technical efficiency. While it was inconclusive whether farrow to finish hog units in the north central sample were more or less technically efficient than those of the southeast sample, estimates of efficiency obtained by the deterministic approach lead to the conclusion that the hog units of the north central sample were operating with relatively less congestion inefficiency (asset fixity) than those in the southeast sample.

Estimates of scale inefficiency obtained by the deterministic methods indicated the hog units in each region were operating with a similar degree of scale inefficiency and the nature of the scale inefficiencies depicted a production frontier relationship dominated by decreasing returns to scale technologies. Estimates for the parameters of the stochastic frontier production function for each region also showed a frontier technological relationship characterized by decreasing returns to scale. It seems reasonable to conclude that the frontier function for hog producers was probably not one of constant returns to scale.

Some authors have indicated that an understanding of technical efficiency in the production process is needed to distinguish between "average" and "best" practices used by producers because firms vary both in use and efficiency of use of various technologies. Inefficient production adversely affects short run profits and in the long run threatens the competitiveness of the firm as a business entity. Results of this study demonstrated that the farrow-to-finish hog units in both the north central and the southeast samples varied in technical efficiency within size categories and across size categories. In both regions, technical efficiency was consistently greater for the larger size hog units.

The explanatory statistical model hypothesized to explain the variation in firm technical efficiency was an attempt to discover why firms varied in technical efficiency. When technological variation among firms is great, a classification of firms into technological groups based on relative technical efficiency would provide a description of firms using homogeneous technologies, and would be useful in production function estimation studies that assume each firm is on the same technological function. Result of the explanatory models were inconclusive relative to the effect of specified hog production practices on technical efficiency. The explanatory variables describing the firm production intensity, the level of use of environment control, the type of farm business organization, management type, type of manure handling system, and type of feed and feed processing gave conflicting results depending on how firm technical efficiency was measured. In Models 1 through 4 these variables collectively showed very little explanation for the variation in technical efficiency as measured by the deterministic approach. In many instances the sign of the estimated coefficients were contrary to expectation or non significant. For Model 5 for both regions, the explanatory variables showed a moderate degree of explanation for the variation in technical efficiency when the dependent variable was a statistical measure of technical efficiency. In this case, the signs of the coefficients estimated for the production practice variables were as expected and technical efficiency was greater for each production practice variable class as compared to the omitted production practice.

The rather wide divergence in estimates of technical efficiency obtained by the alternative frontier approaches was a good indication of the problem posed by choice of the measurement indicator for estimating firm technical efficiency. Further, it was clear that the set of specified explanatory variables describing the use of certain hog production practices was lacking or was in error. Further research of firm technical efficiency is needed to determine which measurement approach is more appropriate and under what circumstances. The existence of technical inefficiency in the hog production process seems quite well documented but the determinants of hog farm technical efficiency are still unclear based on the results of this study.

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