Indivisible and Spatial Components of Dairy Firm Inefficiency

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Abstract

This paper contrasts nonparametric data envelopment analysis (DEA) and free disposal hull (FDH) representations of dairy technology to determine whether factor indivisibilities and firm-specific location components affect economic performance. Location and capital structure variables, in addition to technology and firm structure, are used in a second-stage model to explain firm inefficiency using a Tobit estimator. Capital structure and location factors are correlated with firm efficiency in the DEA models but not the FDH indicating that the FDH representation may account for these factors in the in the first-stage efficiency modeling. Results indicate that failing to control for firm-specific spatial constraints and capital indivisibilities will bias inefficiency estimates and overestimate the potential gains to economic policy designed to improve firm performance.

Indivisible and Spatial Components of Dairy Firm Inefficiency

Limited attention has focused on understanding how farm firm location and capital indivisibilities affect performance. Considerable location research has focused on non-agricultural agglomeration affects across regions and counties (Fujita, Krugman and Venables, 1999; Ciccone and Hall, 1996) and on cities (Fujita, Krugman and Mori, 1999) but little attention has been directed at more disaggregated geographical units of rural character whether they be villages or farms. This is paradoxical given that an agricultural firm's location to its market provided the empirical basis for the beginnings of economic geography (von Thünen, 1966).

Physical capital indivisibilities have been largely relegated to economic engineering studies despite the argument that inefficient usage of physical capital is a component of poor economic performance of established small farms (Tauer and Mishra, 2003). Studies have indicated that a small start-up dairy farm can not compete with large farms (Bailey et al. 1997), that lower milk prices will increase the optimal farm size (Quiroga and Bravo-Ureta, 1992), and economic efficiency of dairy farms is positively correlated with size (Bravo-Ureta and Reiger, 1991). Capitalization levels have been studied for firms but limited research has focused on capital structure and indivisibilities in optimal firm performance or returns to scale.

The causality between dairy farm size and productivity has shown that price-induced expansion has led to productivity gains and embodied technology adoption (Weersink and Tauer, 1991). However, using a stochastic frontier cost curve estimation, efficient small dairy farms have been shown to be competitive with an average 1000-cow farm (Tauer, 2001). Nonetheless, the cost of inefficiency (the difference between the composite and frontier cost functions) for small dairy farms is nearly three times greater than for large farms. The difference between observed production behavior and that of industry leaders on the frontier is of policy interest especially in many states in the Northeast, Lake States and Corn Belt where dairying, a traditional component of their agricultural economy, is disappearing. Determining whether firms are efficient but uncompetitive, or inefficient but potentially competitive, is important to policy-makers concerned with preventing the erosion of agricultural production, agribusiness firms supporting the dairy industry as well the economic activity of farming-dependent areas (Stam et al., 1991). In particular, many traditional dairy states are concerned farm numbers are reaching the lower limit of critical mass where feed companies, bovine veterinarians, other specialized services and dairy processors can find sufficient business volume to justify operation.

This study employs nonparametric frontier modeling and regression analysis to derive the role of capital indivisibilities, spatial and managerial components of firm efficiency. Recently, Alvarez and Arias (2003) investigated the role of human capital constraints in firm performance and found diseconomies of size with fixed managerial abilities in Spanish dairy farms. In this study, a more general inquiry on the impact of factor indivisibilities, embodied technology and spatial components of firm efficiency is developed. Two approaches to efficiency estimation are contrasted to identify the theoretical and empirical tradeoffs in performance modeling. First, alternative nonparametric representations of firm efficiency are contrasted to determine whether factor indivisibilities and spatial heterogeneity can be integrated directly into the efficiency estimation. This is accomplished by modeling firm performance using convex programming techniques and comparing the results to an alternative representation of technology that is monotone but not convex.

This approach is contrasted against a two-stage procedure where location and capital structure is used to explain inefficiency ex-post. Irrespective of the approach followed, location-specific components and firm-level factor indivisibilities affecting firm efficiency are identified to improve the targeting and geographical effectiveness of agricultural policy. Results indicate that failing to control for firm-specific spatial constraints and capital indivisibilities will bias inefficiency estimates and overestimate the gains to economic policy designed to improve performance.

In the following section a comparison of Data Envelopment Analysis (DEA) approaches, employed widely in the agricultural literature, is made with a Free Disposal Hull (FDH) method. This second approach has not been used in agricultural applications despite its appeal in modeling heterogenous, spatially variable and capital-structure-diverse management units characteristic of American farming[1]. Efficiency estimates from both modeling approaches are then subjected to a second-stage decomposition to derive policy-relevant correlates of (in)efficiency using location-specific data combined with capital structure information. Conclusion are discussed in the final section.

Convex and Non-Convex Nonparametric Bounds

Parametric and nonparametric firm efficiency analysis has been widely used in agricultural research to identify factors separating industry leaders from laggards and to incorporate joint production of environmental products into the output mix. Both Färe,

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[1]The FDH approach has been employed in regional and urban economics studies to analyze firm location decisions, public economics to analyze government performance and in management information science to model process indivisibilities.

Grosskopf and Lovell (1994), which focuses on nonparametric approaches, and Kumbakhr and Lovell (2000) on stochastic parametric analyses, provide a comprehensive overview of applications in their respective introductory chapters.

Efficiency analysis is largely concerned with measuring the distance between a frontier generated by industry leaders, who efficiently allocate inputs in a nonwasteful manner, to other producers, not so successful in their optimization process. Identification of the reasons behind the failure to be efficient is related to the manner in which efficient behavior is modeled, since the true production set is unknown, as well as correlates related to input usage and product generation.

Technology representation is posited upon assumptions on the structure of the true, but unobservable, underlying production possibility set. The first component of understanding efficiency modeling using DEA is developed by assuming that there is a set of inputs $x = (x_1, x_2, \ldots, x_n) \in \Re^n_+ = \{x : x \in \Re^n_+, x \geq 0\}$ that can be transformed into a set of outputs $y = (y_1, y_2, \ldots, y_m) \in \Re^m_+$ through a correspondence defined by a production technology $T = \{(x, y) \in \Re^{n+m}_+ : x \in I(x), y \in O(y)\}$ where *I(x)* and *O(y)* are the feasible input and output sets, respectively.

Data on input and output quantities are observed and hence assumes that *T* is nonempty, negative monotonic and closed. This boundary of the feasible technology representation can also be deduced from a set of basic postulates described in Banker *et al.* (1984) and Athanassopoulos and Storbeck (1995) and used to define the returns to scale relationship between inputs and outputs. The postulates include:

P1. (Non-stochastic) *All observed operating units are included in the referent set;*

P2. (Inefficiency) *Free disposability of inputs and strong disposability of outputs*:

$$If \ \ (x, y) \in T \ and \ \bar{x} \geq x \ then \ (\bar{x}, y) \in T(x, y) \in T \ \forall x$$

$$If \ \ (x, y) \in T \ and \ \bar{y} \leq y \ then \ (x, \bar{y}) \in T(x, y) \in T \ \forall y;$$

P3. (Convexity) *For each firm l=(1....L) at or in the interior of the production set, there exists a set of non-negative weights,* θ_l *such that:*

$$\sum_{l=1}^{L} \theta_l = 1, then \left(\sum_{l=1}^{L} \theta_l y^l, \sum_{l=1}^{L} \theta_l x^l \right) \in T$$

Taken together, these three postulates are sufficient to specify a frontier technology as a convex polyhedral set with variable returns to scale as the inner bound of the underlying production possibilities set (Banker and Mandriatta, 1984):

(1) $$T_{VRS} = \left\{ (x, y) \in \Re_{+}^{n+m} | X \geq \sum_{l=1}^{L} \theta_l x^l, Y \leq \sum_{l=1}^{L} \theta_l y^l; \forall \ \theta_j \geq 0; \sum_{l=1}^{L} \theta_l = 1 \right\}.$$

Correspondence between the production possibility set and the technology underlying the set of observation is formally motivated by a detailed proof in Banker (1987). Under these conditions the nonparametric best-practice efficiency frontier can be derived through a piecewise linear envelopment of the data that defines the empirical technology set *(T)* from the observed farm input and output combinations. A firm is technically efficient only when production takes place on the boundary of the feasible technology set.

More restrictive technology bounds can be developed with additional postulates. A nonincreasing returns to scale technology set can be constructed with a fourth postulate that satisfies the monotonicity assumption but partially relaxes the convexity assumption to include the origin as a production possibility.

P4. (Convexity and Partial Proportionality) *Any input-output combination that is not observed on the frontier but is a convex combination of some combinations induced by (P1), and (P2) or some of these plans and the origin of the input-output space.*

This proposition, and the fifth, is summarized Tulkens (1993) and formally presented in Deprins, Simar and Tulkens, (1984). Adding this fourth postulate produces a nonincreasing returns to scale technology set:

$$\textbf{(2)}\ T_{NIRTS} = \left\{(x,y) \in \Re_{+}^{n+m} \mid X \geq \sum_{l=1}^{L} \theta_l x^l, Y \leq \sum_{l=1}^{L} \theta_l y^l; \forall\, \theta_j \geq 0; \sum_{l=1}^{L} \theta_l < 1\right\}.$$

Finally, a full proportionality postulate is proposed to define a constant returns to scale set.

P5. (Full Proportionality) *Any not observed input-output combination that is proportional to some observed plan induced by (P1) and (P2).*

Taken together, postulates one through five produce a cone technology emanating from the origin and implying constant returns to scale. This is the original technology envelope proposed by Farrell (1957) and made operational by Charnes et al. (1978):

$$\textbf{(3)}\ T_{CRS} = \left\{(x,y) \in \Re_{+}^{n+m} \mid X \geq \sum_{l=1}^{L} \theta_l x^l, Y \leq \sum_{l=1}^{L} \theta_l y^l; \forall\, \theta_j \geq 0\right\}.$$

Under these three specifications of the production technology, inefficient producers lying in the interior are projected onto the frontier surface as a convex combination of efficient units.

If a vector of nonnegative output prices p is known, and the output set is nonempty and compact as defined above, a revenue function can be developed to represent an output-price characterization of technology viz $D(P,Y,T) = \max_{y}\{py: y \in O(Y)\}$ or if a vector of input prices

r are known and the input set is nonempty and closed, a cost function representation of technology is possible as $C(Y,R,T) = \min_{x}\{rx: x \in I(x)\}$. Formal motivation is provided in

Färe *et al.*(1993) and not duplicated here.

Based upon the cost representation above, a measure of input-oriented allocative efficiency can be deduced as the ratio of observed cost to the cost of production *had* the producer been technically efficient. Scale efficiency, measured in terms of ray average cost, can be deduced from the ratio of the efficiency index generated under the constant returns to scale assumption to the variable returns measure. Economic efficiency is defined as the product of technical, scale and allocative efficiency. All efficiency measures are bounded from below (0,1]. Proportionate cost or input savings can be measured as the difference between being efficient and the firm's score while the proportionate overuse of factors as the inverse of the score.

Incorporating Indivisible and Spatial Components into Efficiency Measurement

Most efficiency studies have ignored firm-specific access to resources and markets, thereby dismissing potential pecuniary externalities and instead relying upon the assumption of the "law of one price" (Bravo-Ureta and Rieger, 1991; Chavas and Aliber, 1993; Fletschner and Zepeda, 2003). Firm-level spatial heterogeneity has also ignored site-specific resource endowments thereby limiting insight into capital configuration constraints. Parametric studies have incorporated intercept-shifting dummy variables to identify county-, state- or regional level differences without identifying the cause behind the difference.

Projection of inefficient producers onto a representation of the frontier, and derivation of the gains to be made from increased efficiency, are made upon the assumption that producers face a homogenous, or more general homothetic, ray-homogenous or ray-homothetic, production functions. In most cases, inefficient levels of inputs or outputs (or a combination of both) are radially scaled, in constant proportionate terms, towards the frontier to derive the relative changes required to become technically or allocatively efficient[2]. However, there are few empirical examples where firms maintain constant factor proportions during expansion to achieve scale efficiency as cited in over fifty years of production research spanning Chamberlin (1948) to Tone and Sahoo (2003).

Pecuniary externalities, firm location and capital indivisibilities have recently been used to illustrate where the proportionality assumption is a strong restriction preventing useful insight into nontrivial production settings and inefficient firm performance (Tulkens, 1993; Athanassopoulos and Storbeck, 1995). The "Free Disposal Hull" model, first described by McFadden (1978) and empirically implemented by Deprins et al. (1983) is argued to be a more relevant representation of technology when input and output prices faced by producers are dependent upon quantity and the price-taking assumption is not valid, when ex ante resources allocation decisions are imperfect or price transmission is imperfect (Cherchye et al, 2000).

Secondly, the FDH approach has been employed to evaluate the relative efficiency of discrete siting decisions ex-ante or conversely the inefficiency associated with discrete siting decisions ex-post (Athanassopoulos and Storbeck, 1995). Spatial siting decisions are associated

[2]While most studies radially expand output or contract inputs to derive measures of efficiency, Chavas and Cox (2000) have proposed a simultaneous rescaling of both as a more generalized measure of Shephard's distance function.

with access or distribution costs related to a location and hence influence absolute and relative prices facing individual producers. Thirdly, Tone and Sahoo (2003) argue that a non-convex representation of technology embedded in the FDH representation addresses capital indivisibilities or "lumpiness" associated with process indivisibilities and hence nonhomogenous production functions. In particular, increasing returns to scale is impossible unless there is an indivisibility in one or more inputs.

The FDH reference set is developed by relaxing postulates (3)-(5) and by noting that the remaining two postulates are sufficient to induce a reference set consistent with economic theory, especially in the economically meaningful region of production where marginal costs of inputs and marginal revenues of outputs are nonnegative. It is constructed as a step-wise frontier with each facet orthogonal to the adjacent. The FDH technology can be represented as:

$$\textbf{(4)}\ T_{FDH} = \left\{ \begin{array}{l} (x,y) \in \Re_{+}^{n+m} | X = X^{l} + s^{-}; Y = Y^{l} - s^{+}; (X,Y) \in T \cup \{(0,0)\}; \\ s^{-} \in \Re_{+}^{n}, s^{+} \in \Re_{+}^{m} \end{array} \right\}$$

where s^{-} and s^{+} are slack variables.

Taken together, the coarsest representation of technology will be the constant returns to scale technology (postulates 1 to 5) followed by the nonincreasing returns to scale (postulates 1 to 4), the variable returns to scale (postulates 1 to 3) and finally the free disposal hull, the most parsimonious, by (1 and 2) as represented in Figure 1. Cost function representations of technology, in single output space, are presented with the DEA constant returns to scale representation depicted by the ray line 0I, the DEA variable returns by the polyhedral hull GHIJ, the nonincreasing returns to scale cone (not labeled on the graph) as 0IJ and the FDH as dashed stepwise progression of orthogonal facets GhkImJ. The graphical representation reinforces the inverse relationship between the “coarseness” of the technology and the parsimony of the technology assumptions. Defining which technology is the most accurate in representing a particular industry can devolve to an empirical question.

This question can be approached with two distinct approaches. Traditional DEA approaches can be employed to determine technical, allocative, scale and economic efficiency. Hypothesized correlates of inefficiency can be regressed against these scores and corrected for state-conditional factors impacting efficiency (Sherlund et al, 2002). The second approach is to incorporate capital indivisibilities and spatial components directly into the efficiency analysis in order to control for these predetermined factors using the FDH approach. Both approaches are contrasted in the following section.

Assessing DEA and FDH Efficiency of Dairy Farms

The nonparametric approaches discussed in the previous section are applied to a cross sectional sample of dairy firms. Maine has a diverse physical geography with producers located throughout the state and service centers clustered on the main north-south interstate (Figure 2). All dairy farms in the state are presented to preserve the anonymity of respondents. Milk that is produced, processed and sold in the state is not under the regulation of the Federal Milk Marketing Order, and regulated by a quasi-governmental commission that has the jurisdiction to regulate producer premiums. It is in their mandate to regulate premiums based upon location, similar to the Federal marketing orders over national production. There are several factors motivating a more targeting investigation into the spatial components of firm inefficiency in Maine.

Economic service centers for agriculture are located in the south and south-central part of the state as are the largest dairy processors. Producers to the north, northwest and west face higher transaction costs when procuring inputs and marketing products. At the same time, the southern part of the state is experiencing the greatest growth in non-agricultural land development. Many cities and townships in this region face increasing population and housing growth, higher tax rates for services and a different composition of employment alternatives. Thirdly, biophysical production potential differs throughout the state related to physical geography. As one moves from south to northeast, and towards the Appalachian mountains, growing degree days decrease and the potential of producing concentrated feeds, namely grain corn, and corn forage decreases. However, the region between the coast and the Appalachians mountains is more drought prone than other areas.

Previous studies have disaggregated efficiency analyses into state or district level sub-studies thereby implicitly assuming a homogenous production technology by region but allowing variation across regions or district (Chavas and Aliber, 1993; Fletschner and Zepeda, 2002). This approach limits insight into the source of location-specific correlates of inefficiency and determining whether agricultural policy can play a more targeted role in rural economic development. In an ex-ante perspective, greater information on whether these factors affect business performance can aid strategic firm location decisions.

A second consideration of this study is determining whether capital structure, apart from gross measures of scale, affect firm performance. In particular, it is crucial to understanding the role of technology, physical, human and social capital indivisibilities in order to accurately diagnose strategies to improve economic performance or to advocating a less painful transition from dairy production into another type of farming or non-agricultural income generating activities.

This study relies upon a unique georeferenced farm-level data set that permits investigation into location and capital indivisibility factors affecting firm decisions. The data used in the analysis were collected in 2002 by the Maine Milk Commission (MMC) for the purpose of establishing a state-level cost of production estimate. The survey was sent to all dairy producers in the state of Maine and georeferenced to determine whether differences in physical geography contribute to economic performance. The survey instrument was developed to test whether economic geography impacts firm performance with specific questions written to elicit location information on firm input purchases and associated transaction costs. This instrument is rich in firm level data especially in areas not captured by most farm management surveys. Survey-derived information was combined with GIS-derived data.

Data used in efficiency estimation involves multiple outputs and inputs of dairy firms. The outputs used in this analysis includes three categories (1) milk, (2) livestock and (3) crops. All outputs are measured as the aggregate value of the products produced in each category. This was necessary to control for differing component values of butterfat, proteins and other solids in milkm-specific premiums and deductions in the milk check as well as diverse portfolios of livestock and crop sales. The inputs include (1) cows, (2) land, (3) buildings, (4) equipment, (5) forage, (6) concentrated feed (7) veterinary services and health products, (8) “other”cash expense, and (9) labor. All prices were measured at the firm level. Capital inputs, including cows, land, buildings, and equipment are valued as stocks in the technical efficiency estimation and as annual flows in the cost estimates. The stocks were converted to flows by calculating annual equivalent annuities based upon a 5.7% real interest rate and a 25% cull rate for cows, an infinite lifespan for land, and 20- and 10-year useful lives for buildings and equipment respectively. Summary statistics of the outputs and inputs used in study are presented in Table 1.

The relative technical efficiency of each firm was investigated using input-oriented DEA methods under the assumption of variable, nonincreasing and constant returns to scale, in addition to the nonstochastic and free disposability postulates. The variable returns to scale DEA model is constructed from a linear programming model of equations 5, 6, 7, 8a, 9a and 10, the nonincreasing returns to scale model from 5, 6, 7, 8b, 9a and 10, the constant returns to scale model from 5, 6, 7, 9a and 10. The FDH technical model is developed from 5, 6, 7, 9b and 10.

$$(5)\quad \min_{\lambda,\theta} \sum_{l=1}^{L} \theta_l$$

$$s.t.$$

$$(6)\quad \sum_{l=1}^{L} \lambda_l Y_m^l \geq Y_m^{l0} \;\; \forall\, m \in M; l \in L$$

$$(7)\quad \sum_{l=1}^{L} \lambda_l X_n^l \leq \theta_l X_n^{l0} \;\; \forall\, n \in N; l \in L$$

$$(8a)\quad \sum_{l=1}^{L} \lambda_l = 1$$

$$(8b)\quad \sum_{l=1}^{L} \lambda_l \leq 1$$

$$(9a)\quad \lambda \geq 0$$

$$(9b)\quad \lambda \in \{0,1\}$$

$$(10)\quad \theta \geq 0$$

$$(11)\quad \min_{\lambda,X} \sum_{l=1}^{L} \sum_{n=1}^{N} r_n^l X_n^l$$

$$s.t.$$

$$(12)\quad \sum_{l=1}^{L} \lambda_l Y_m^l \geq Y_m^{l0} \;\; \forall\, m \in M; l \in L$$

$$(13)\quad \sum_{l=1}^{L} \lambda_l X_n^l \leq X_n^{l0} \;\; \forall\, n \in N; l \in L$$

$$(14a)\quad \sum_{l=1}^{L} \lambda_l = 1$$

$$(14b)\quad \sum_{l=1}^{L} \lambda_l \leq 1$$

$$(15a)\quad \lambda \geq 0$$

$$(15b)\quad \lambda \in \{0,1\}$$

The cost correspondence for the variable returns to scale case is constructed from 11, 12, 13, 14a, and 15a, the nonincreasing returns to scale cost model from 11, 12, 13, 14b, and 15a, and the constant returns to scale models from 11, 12, 13, and 15a. The FDH cost model is written 11, 12, 13,and 15b. The FDH models can be implemented using mixed integer programming, a weak sorting algorithm (described in Tulkens, 1993) or a combination of both. This study employed the third approach.

Scale efficiency for the firm is defined by dividing the results of constant returns to scale cost model by the variable returns model. The nonincreasing returns to scale model is used to determine whether the scale inefficient firm is operating in a region of increasing or decreasing returns to scale. The Farrell allocative efficiency index can be determined by dividing the cost function results by the observed cost if the firm had been technically efficient viz: $AE(Y,R,T)=C^*(Y,R,T)/[R'X(TE)]$. Finally, economic efficiency is determined as the product of technical, allocative and scale efficiency.

Results of the nonparametric efficiency estimates are provided in Table 2. Using the convex DEA representation of technical efficiency, the majority of firms (58%) are fully efficient and the average efficiency score is also very high at 89%. Under the FDH representation, all firms are technically efficient. While most firms are technically adept at producing output, there are considerable cost savings due to reallocation of inputs according to the DEA definition of allocative efficiency. Using the DEA representation of allocative efficiency under variable returns to scale, only seven percent of the firms are fully efficient and, on average, only 52% efficient in allocating costs. Cost savings are to be had also under the FDH estimate but there is a significant difference in the magnitude of the mean difference (t=15.5, p<0.01). Over half of the firms are allocatively efficient under the FDH definition and the overall average is 88% efficient.

Assuming half-normal distributed efficiency scores, the DEA constant returns to scale technology specification is rejected in factor of DEA variable returns using Banker’s (1996) scale test for technical and cost presentations at the 99% level of significance (F(92,92)=2.38 and 1.71, respectively). Only 3% of the firms are scale efficient. Most scale inefficient firms, 91.3%, are operating at a point of increasing returns to scale under the DEA models. When overall economic efficiency is calculated, only three percent of the firms are efficient and the overall average is reduced to 32%. As all firms are technically and scale efficient under the FDH representation, the economic efficiency score is identical to the allocative score. A comparison of the difference between the means of economic inefficiency scores, as calculated by the DEA and FDH approaches, is significant (t=29.1, p<0.01).

These results point to strong differences in policy implications. The DEA approach indicates that there are large inefficiencies in cost structure when firms are evaluated in relation to a globally attainable aggregate cost, or average cost function enveloping short-run average cost. In fact nearly ninety percent of all firms are operating in a range of increasing returns to scale. However, Färe and Primont (1988) show that when the law of one price does not hold, DEA-based cost efficiency estimations provide a lower limit of “true”efficiency. On the other hand, the FDH approach implies that all firms are technically efficient given firm-specific production possibilities and resource endowments. The monotone but nonconvex average cost structure does not indicate large allocative or economic inefficiency when capital indivisibilities and spatial components are directly integrated into firm cost structure.

Correlates of Firm Inefficiency

In order to test whether the FDH approach is capturing firm-specific constraints, a second-stage econometric model is used to identify correlates of inefficiency. These correlates are broadly classified into managerial, capital and location factors. “Managerial” factors contain both business, farmer and farm technology factors. Most second stage regressions on firm inefficiency attempt to explain performance with similar variables and add location dummy variables (Bravo-Ureta and Rieger, 1991). In this study, these traditional variables are augmented with capital structure information subdivided into physical and social components, and location factors broken into business, civic and biophysical factors.

Farm-specific managerial and business structure variables include whether the firm was organized as a sole proprietorship or not (Legal Structure), whether a milking parlor is employed (Milking System), whether the firm produced for the conventional or organic market (Organic), used pasture as the primary source of forage during the grazing season (Pasture), or used rBST (Posilac). These variables takes on a value of one if the firm is not organized as a sole proprietorship, if they use a parlor, produce for the organic market, rely upon pasture and use rBST. Characteristics of managerial skill are captured by the age of the owner/operator (Age), the highest level of attained education(Education), and the length of time operating the farm as the manager (Experience).

Capital structure variables are divided into two subcategories, physical and social. Physical capital variables are targeted at determining whether capital structure of the farm affects the efficiency score. These variables include the total values of farm assets per cow (Assets per Cow), land base per cow (Land), and three (of four) capital shares: the share of capital invested in cows (Share Cows), buildings (Share Buildings) and equipment (Share Equipment). Excluded is the share for land. Most of these farms were established in the early to mid-twentieth century when pasture played an important role in dairy production systems. As dairy production shifted towards better management of cow nutrition, the importance of land for pasture has diminished. Hence a high land to cow ratio, or a higher share of capital assets in land may be an inefficient capital allocation strategy.

Social capital is measured indirectly as the number of dairy farms within a ten mile radius of the farm observation (Farms <10 miles), between ten and fifteen miles (Farms 10-15 miles) and between fifteen and 20 miles (Farms 15-20 miles). Each category is mutually exclusive. It is hypothesized that the greater number of farms within a specific area, the greater the opportunities for mutual sharing of equipment, knowledge and other factors of production. The rings are created in order to test the secondary hypothesis of declining importance as interfarm distance increases.

Location specific factors are subdivided into three categories: business, civic and biophysical subcategories. Location specific transaction costs are captured by measures of distance between farms and their primary suppliers of veterinary services (Vet Distance), other herd health inputs (Health Distance) and the source of concentrated feed (Feed Distance). It is hypothesized that greater distance may generate inefficient factor usage by introducing unpriced transaction costs in service or product provision. The location where these service and products are provided may be another discriminating factor. Consistent with the agglomeration literature (Fujita, Krugman and Venables, 1999) where larger economies with greater competition for production factors have higher costs, goods or services purchased from these areas may generate additional costs. At the same time, greater competition between input suppliers in larger service centers may place downward pressure on prices. These variables, "Vet Location," "Health Location," and "Feed Location" are measured by the total amount of annual retail sales in the purchase location.

Civic location factors are related to local and township level economic conditions. Variables include the tax mill rate (Mill rate), unemployment rate (Unemployment rate) and the annualized percent increase in housing development in the preceding decade (Housing development). Higher mill rates increase the cost of holding capital when municipalities revalue tax rates. Higher unemployment rates are hypothesized to decrease the cost of labor while greater housing pressure increases the opportunity cost of retaining land in agriculture. Finally, biophysical location factors are measured by the total number of growing degree days (GDD) from June to September to measure the suitability of growing corn grain and forage. Productivity is positively correlated with GDD. Four monthly rainfall totals (June, July, August and September rainfall) are used to determine whether rainfall impacts firm efficiency. In general, more rainfall is better, but too much early or late season precipitation could create production bottlenecks and untimely crop management activities. Summary statistics of the explanatory variables used in the regressions are presented in Table 3.

As several farms are efficient, this necessitates a censored regression model:

$$\textbf{(16)}\quad \begin{aligned} &\ln(\eta^{*}) = \gamma + M\alpha + C\psi + S\delta + e \quad if\ \gamma + M\alpha + C\psi + S\delta + e > 1 \\ &\ln(\eta^{*}) = 1 \quad otherwise, \end{aligned}$$

where η^{*} is the l[th] firm's inefficiency score, defined as the inverse of the distance function measuring inefficiency (η^{*}=1/θ), M is a LxM matrix of managerial variables, C is a LxC matrix of capital structure variables, S is a LxS matrix of location-specific variables, α, ψ, and δ are Mx1, Cx1 and Sx1 vector of parameters to be estimated, γ is a scalar, and e is a vector of residuals. If the estimator is tobit, the log-likelihood function can be written:

$$\textbf{(17)}\quad \begin{aligned} LL = &\sum_{\theta>1} -1/2\left[\ln(2\pi) + \ln\left(\sigma^{2}\right) + \frac{(\ln(\eta^{*}) - \gamma - M\alpha - C\psi - L\delta)^{2}}{\sigma^{2}}\right] \\ &+\sum_{\theta=1}\log\left[1 - \Phi\left(\frac{\gamma - M\alpha - C\psi - L\delta}{\sigma}\right)\right], \end{aligned}$$

where the first term is a maximization of the nonlimit observations, and the second for those efficient firms found at the limit. The model is estimated by maximizing the log-likelihood function of the n[th] firm with respect to α, ψ, δ and γ. Four sets of inefficiency scores (η^{*}) are evaluated against the common set of regressors: DEA representations of technical, allocative and economic inefficiency and the FDH economic inefficiency measure. In addition a constructed model of the difference between the DEA and FDH economic inefficiency scores is estimated. Parameter estimates and their standard errors for the five regressions are presented in Table 4. In addition, Table 5 presents joint tests of significance of the managerial, physical and social capital variables, the business, civic, and biophysical location factors as well as a likelihood ratio test of the full model against one that only contains the managerial characteristics commonly found in other farm efficiency analyses.

Likelihood ratio tests indicate that models not incorporating capital and location factors will suffer from omitted variable bias, except when analyzing technical or FDH efficiency. No one group of explanatory variables was significant in all regressions but all categories were significant in at least one regression.

Firms that were legally structured as anything but sole proprietorships improved economic and FDH efficiency. Unlike Bravo-Ureta and Rieger (1991), experience was not statistically significant. Physical capital structure variables were significant in all DEA models but not in the FDH model. Firms relying upon pasture improved allocative efficiency but this variable did not affect technical or economic performance.

The greater land per cow owned by the firm, the less technically and allocative inefficient was the firm. This reinforces the role of the farm's land base for use as pasture and may indirectly signal merit as a production strategy. A higher land per cow ratio did not significantly influence economic efficiency indicating that land extensive-based production strategies may not be appropriate once scale factors are incorporated. All DEA efficiency measures were positively correlated with the share of financial capital invested in cows and this variable has the greatest impact upon improving firm efficiency scores[3]. Increasing this share of capital necessitates the purchase of discrete animal units or the sale of lumpy equipment or land parcels. Only one social capital variable relating the farm other farms was significant. Economic inefficiency decreased the more farms within a radius of 10 to 15 miles.

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[3]This was determined by a McDonald and Moffit transformation of the tobit estimates into a decomposition of the marginal impact upon the intensity of inefficiency, conditional upon whether or not the firm was inefficient. This decomposition is available from the author upon request.

Several location specific variables explained the variation in DEA scores. Business location factors were correlated with allocative and economic efficiency. The further a producer traveled to purchase health inputs the more allocatively inefficient. No consistent sign was found on the location of where the inputs were purchased. If veterinary services were based in a town with large retail sales, allocative inefficiency decreased. If concentrated feed was purchased from a larger service center, technical and economic inefficiency increased. Civic factors, including the mill rate and the unemployment rate were correlated with inefficiency. Higher mill rates were negatively correlated with technical and economic inefficiency while higher unemployment increased technical efficiency. Finally, two biophysical factors affected economic efficiency: June and September rainfall. Economic inefficiency was positively correlated with rainfall in these two months.

By contrast, only one managerial variable was significantly related to the FDH measure of economic efficiency. No capital or location variables explained inefficiency calculated by the nonconvex FDH model indicating that the FDH model captures micro-variation in production technology. In order to support this finding, one final regression was estimated to correlate these factors with the difference between DEA and FDH economic efficiency scores. The difference can be interpreted as the distance between the aggregate envelope cost curve and the stepwise curve. If a firm produced for the conventional market, the FDH score was closer to the DEA. In addition, the more dairy farms between 10 to 15 miles of the producer, whether a producer purchased feed from a large service center, and the greater the rainfall during August, the closer the FDH measure to the DEA score. By contrast, the difference between DEA and FDH estimates were positively related to the share of capital in buildings, closely neighboring farms within 10 miles, and rainfall occurring in June. Capital and spatial factors explain the difference between the scores.

Concluding Comments

This paper extends the FDH methodology into the agricultural economics literature and compares it to DEA approaches to measure dairy firm efficiency. Results from the comparative analysis indicate that the two methods produce statistically different results. Significantly less cost savings can be had if the true underlying production technology is represented by the FDH than by the DEA variable returns formulation.

Several authors argue that the FDH approach is more appropriate where economic geography or firm structure affects the prices that one pays for input or receives from outputs. Secondly, capital indivisibilities may also justify the usage of a production or cost frontier that is nonconvex but monotone. DEA technical, allocative and economic inefficiency scores were regressed on managerial, capital and location factors. Results indicated that capital structure and location variables explained variation in DEA inefficiency scores but not FDH. Differences between DEA and FDH scores were also explained by capital and location variables indicating that a convex representation of frontier efficiency will bias inefficiency estimates and overestimate the potential gains to economic policy designed to improve firm performance. In particular DEA efficiency scores are most sensitive to physical capital structure variables. This finding is additive to our knowledge about the correlates of farm efficiency. Historically, previous studies have focused on scale, farm and farmer characteristics.

As stressed by several authors including Lovell and Vanden Eeckaut (1994), inefficient firms in the FDH approach are projected onto an orthant spanned by a single efficient producer that is weakly dominating in cost and output. This actual producer can be used a peer role model for the inefficient firm but a peer under the DEA approach will likely be represented as a convex combination of several efficient firms and hence "fictitious." Identification of a true peer as a role model has useful implications for extensionists and policy makers rather than a hypothetical convex combination of firms that assumes factor divisibilities and a homogenous production technology.

Farming systems are inherently diverse, slow to adjust capital, and constrained by establishment conditions that were made without perfect foresight. These conditions, for this sample of dairy producers, illustrates the impact of economic geography and the tradeoff between the production of dairy products and broader rural economic policy. The results of the DEA analysis indicates that many of these farms are grossly inefficient and should restructure physical capital and location to improve cost effectiveness or exit. Accepting the FDH approach indicates that these farms are much more efficient, given nonhomogenous resource endowments, and diverse. State-conditional estimates of DEA efficiency should be calculated to determine the relative contribution of capital inefficiencies and the relative spatial efficiency of location choice. In addition, future research should develop stochastic applications of FDH analysis or incorporate spatial components into stochastic parametric efficiency modeling.

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Table 1. Data summary for outputs, input and firm-specific prices

	Mean	Standard Deviation
Outputs		
Milk Sales ($)	343,783	593,141
Crop Sales ($)	3,165	9,519
Livestock Sales ($)	14,568	24,297
Inputs		
Cows (milking cows)	106	162
Land (acres)	512	422
Buildings ($ stock)	218,298	220,673
Equipment ($ stock)	177,900	293,714
Forage (tons)	2,417	4,944
Concentrates (tons)	466	1,024
Veterinary (annual visits)	18	23
Cash ($)	61,700	94,361
Labor (hours)	8,080	7,605
Prices ($/unit)		
Cows ($ annual service flow)[1]	354	103
Land ($ annual service flow)[1]	40	20
Buildings ($ annual service flow)	18,571	18,773
Equipment ($ annual service flow)	23,828	39,341
Forage ($/tons)	28	68
Concentrates ($/tons)	220	284
Veterinary (per visit expense)	675	504
Labor (hourly wage)	5.93	4.55

[1]Annual flow values correspond to mean reported prices of cows of $1236/cow and $702/acre.
N=92

Table 2. Efficiency scores under alternative model assumptions

	Mean	Standard Deviation	Skewness	Kurtosis	Min	Max	% Efficient
DEA							
Technical	0.887	0.165	-1.262	0.310	0.430	1	58
Allocative	0.520	0.194	1.110	0.789	0.222	1	7
Economic	0.315	0.187	1.765	4.207	0.059	1	3
FDH							
Technical	1	-	-	-	1	1	100
Allocative	0.878	0.184	-1.438	0.982	0.273	1	52
Economic	0.878	0.184	-1.438	0.982	0.273	1	52
Difference (FDH-DEA Economic)	0.562	0.186	-1.077	1.313	0	0.85	3

N=92

Table 3. Descriptive statistics of the correlates of dairy firm inefficiency

	Mean	Std. Deviation
Legal Structure (0=Sole Proprietor)	0.46	0.50
Milking System (0=Stanchion)	0.39	0.49
Organic (0=Nonorganic)	0.05	0.23
Pasture (0=Not important)	0.61	0.49
Posilac (0=Not used)	0.08	0.27
Age (Years)	53.49	11.10
Education (Years attained)	13.10	2.19
Experience (Years)	24.25	12.39
Assets per Cow ('000 $/cow)	6.07	2.89
Land (Acres/cow)	6.99	5.10
Share Cows (%)	0.14	0.07
Share Buildings (%)	0.28	0.17
Share Equipment (%)	0.17	0.13
Farms <10 miles (#)	14.40	7.32
Farms 10-15 miles (#)	20.83	11.09
Farms 15-20 miles (#)	24.87	12.33
Vet Distance (miles)	19.91	10.97
Vet Location (‘00 $million retail sales)	0.93	1.44
Health Distance (miles)	10.12	8.51
Health Location (‘00 $million retail sales)	0.47	1.31
Feed Distance (miles)	53.59	46.25
Feed Location (‘00 $million retail sales)	3.36	3.04
Mill rate (%)	1.72	0.50
Unemployment rate (%)	5.36	2.16
Housing development (% change from 1990 to 2000)	17.0	11.0
Growing degree days	512.95	38.16
June rainfall (inches)	3.68	0.23
July rainfall (inches)	3.39	0.25
August rainfall (inches)	3.61	0.30
September rainfall (inches)	3.43	0.24

n=92

Table 4. Tobit estimates of the factors affecting firm inefficiency

	DEA						FDH		Economic	
	Technical		Allocative		Economic		Economic		Difference	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Legal Structure	0.434	0.344	0.052	0.268	-0.630**	0.272	-0.577*	0.322	0.139	0.268
Milking System	-0.298	0.334	-0.313	0.267	-0.275	0.266	-0.240	0.320	-0.264	0.266
Organic	0.887	0.718	0.950	0.614	0.170	0.602	1.051	0.662	-1.490**	0.613
Pasture	-0.302	0.354	-0.840***	0.294	-0.316	0.288	0.154	0.333	-0.151	0.286
Posilac	0.892	0.616	0.779	0.537	0.511	0.534	0.081	0.629	0.019	0.533
Age	0.025	0.027	0.016	0.020	-0.007	0.020	-0.015	0.024	0.018	0.020
Education	0.106	0.066	-0.053	0.053	-0.018	0.053	-0.063	0.062	0.002	0.053
Experience	0.017	0.022	-0.004	0.017	0.013	0.017	0.016	0.020	-0.006	0.017
Assets per Cow	-0.071	0.083	-0.049	0.066	0.004	0.066	0.055	0.073	-0.053	0.066
Land per cow	-0.075*	0.042	-0.061*	0.034	-0.002	0.033	-0.016	0.039	0.022	0.033
Share Cows	-11.038***	4.076	-6.663**	2.928	-6.759**	2.926	-3.102	3.445	-2.828	2.887
Share Buildings	0.523	1.239	-1.070	0.973	0.299	0.967	-1.248	1.115	1.851*	0.976
Share Equipment	0.664	1.766	-0.585	1.298	1.446	1.300	0.758	1.514	1.021	1.297
Farms <10 miles	0.000	0.027	0.011	0.022	0.032	0.022	-0.022	0.025	0.067***	0.022
Farms 10-15 miles	0.003	0.019	-0.018	0.015	-0.027*	0.015	-0.004	0.017	-0.031**	0.015
Farms 15-20 miles	-0.026	0.017	-0.021	0.013	-0.012	0.013	-0.015	0.015	0.015	0.013
Vet Distance	0.004	0.016	0.017	0.013	0.013	0.013	0.019	0.015	-0.004	0.013
Vet Location	-0.158	0.207	0.264*	0.137	0.040	0.135	0.009	0.156	0.060	0.135
Health Distance	0.011	0.019	0.026*	0.015	0.019	0.015	0.003	0.017	0.019	0.015
Health Location	-0.163	0.201	-0.038	0.136	0.150	0.136	0.104	0.151	-0.075	0.136
Feed Distance	-0.005	0.004	-0.008**	0.003	-0.006*	0.003	-0.004	0.004	0.001	0.003
Feed Location	0.036	0.062	0.054	0.046	-0.033	0.046	0.020	0.054	-0.086*	0.046
Mill rate	-0.635*	0.372	-0.022	0.287	-0.539*	0.290	-0.057	0.331	-0.333	0.287
Unemployment rate	0.210**	0.099	0.105	0.083	0.032	0.082	-0.088	0.098	0.091	0.083
Housing development	1.682	1.635	2.013	1.324	-0.880	1.315	0.544	1.534	-0.589	1.313
GDD	-0.002	0.008	-0.006	0.007	0.003	0.007	0.004	0.007	-0.003	0.007
June rainfall	1.576	1.012	1.243	0.784	1.502*	0.784	0.123	0.880	1.544*	0.784
July rainfall	-0.279	0.823	0.440	0.694	0.546	0.694	0.268	0.786	0.248	0.693
August rainfall	-1.208	0.936	-0.598	0.730	-0.577	0.727	0.837	0.836	-1.465**	0.733
September rainfall	0.411	0.920	1.071	0.759	1.338*	0.759	1.329	0.872	-0.535	0.754
Constant	-1.656	8.442	-0.140	6.910	-5.595	6.906	-8.370	7.937	4.826	6.905
Dependent Variable	3.038***	0.386	3.509***	0.273	2.460***	0.186	3.033***	0.355	6.758***	0.513
Log Likelihood	-35.51		-21.65		-49.95		-40.29		39.00	
Squared Correlation	0.29		0.41		0.49		0.47		0.40	

Significant at the *=10%, **=5% and ***=1% level.

Table 5. Joint tests of significance on inefficiency scores

	DEA			FDH	
	Technical	Allocative	Economic	Economic	Economic Difference
Joint tests of significance					
Managerial (df=8)	14.67 *	14.03 *	11.58	9.92	10.16
Physical Capital (df=5)	9.54 *	7.00	13.53 **	4.81	6.29
Social Capital (df=3)	2.51	4.51	4.87	2.70	11.55 ***
Business Location (df=6)	3.62	15.87 ***	8.77	3.47	5.27
Civic Location (df=3)	9.17 **	3.41	3.69	1.25	2.71
Biophysical Location (df=5)	4.56	12.70 **	10.18 *	5.43	6.05
Likelihood ratio of full model versus restricted (managerial only)	26.98	37.42 **	54.64 ***	30.16	37.03 **

Significant at the *=10%, **=5% and ***=1% levels.

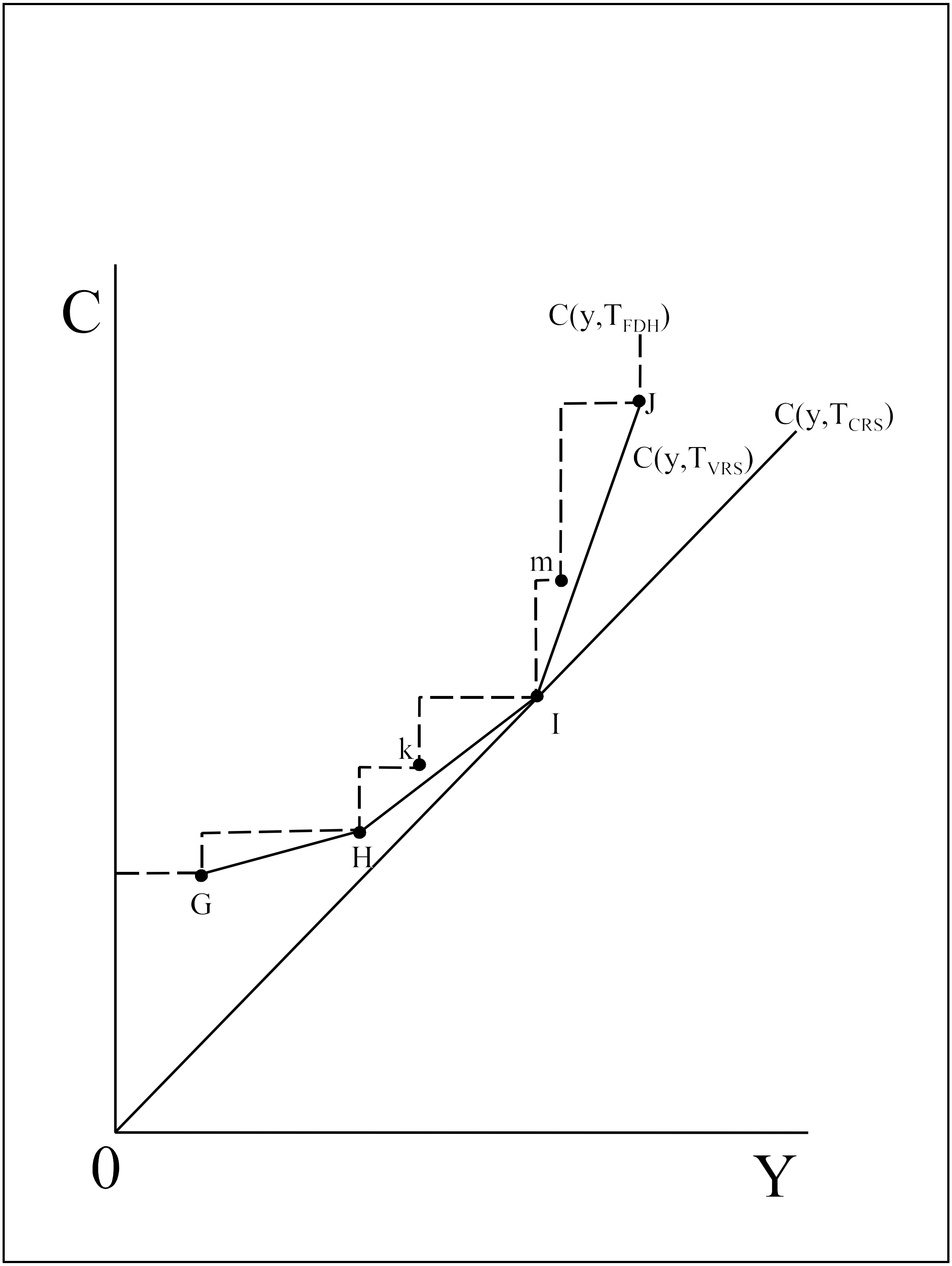

Figure 1. Alternative technology representations of cost frontier with free disposability

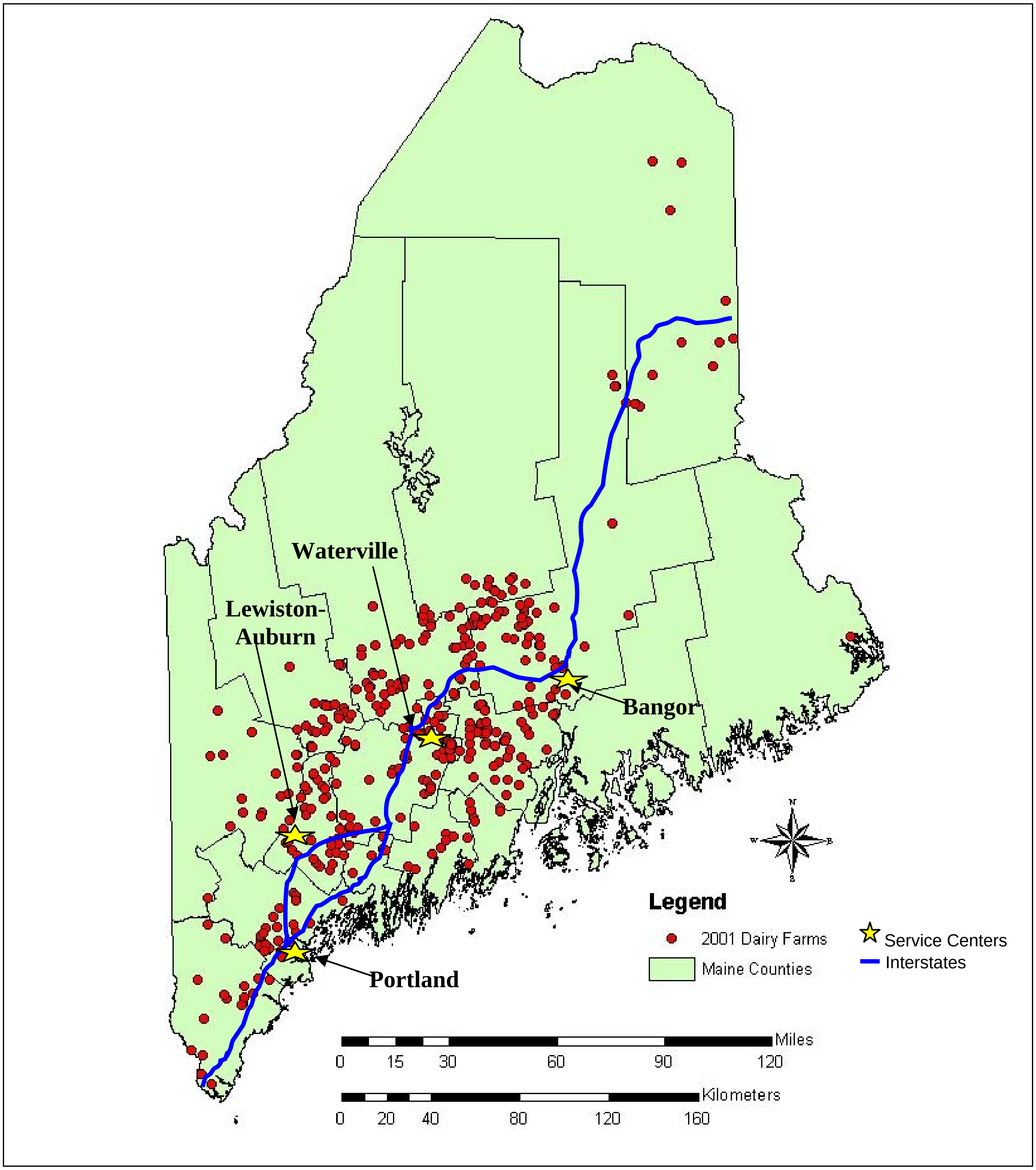

Figure 2. Geographic location of Maine dairy firms and primary service centers