TECHNOLOGIES AND LOCALIZED TECHNICAL CHANGE

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Abstract
This contribution is based on the notion that different technologies are present in an industry. These different technologies result in differential "drivers" of economic performance depending on the kind of technology used by the individual firm. In a first step different technologies are empirically distinguished. Subsequently, the associated production patterns are approximated and the respective change over time is estimated. A latent class modelling approach is used to distinguish different technologies for a representative sample of E.U. dairy producers as an industry exhibiting significant structural changes and differences in production systems in the past decades. The production technology is modelled and evaluated by using the flexible functional form of a transformation function and measures of first- and second-order elasticities. We find that overall (average) measures do not well reflect individual firms' production patterns if the technology of an industry is heterogeneous. If there is more than one type of production frontier embodied in the data, it should be recognized that different firms may exhibit very different output or input intensities and changes associated with different production systems. In particular, in the context of localized technical change, firms with different technologies can be expected to show different technical change patterns, both in terms of overall magnitudes and associated relative output and input mix changes. Assuming a homogenous technology would result in inefficient policy recommendations leading to suboptimal industry outcomes.

Keywords - Heterogenous Technologies, Transformation Function, Localized Technical Change
JEL - Q12, O33, C35

Introduction[i]

In most industries different firms operate with different technologies or production systems. Recognizing these differences is key to understanding structural change, which is likely to involve varying technical change patterns for different systems or movements toward different systems. That is, as an industry evolves, technical change does not just increase the amount of output possible from a given amount of inputs (productivity growth) and induce substitution among inputs (technical change biases), as is traditionally recognized in productivity analysis. It also involves new production systems with different characteristics in terms of output and input mix, which may be in the form of a continuum with discrete changes or may involve entirely different production frontiers. The presence of different technologies in an industry means that empirical analysis of technical change, and its drivers and effects, is more complex than is typically modeled by shifts and twists in a common production frontier or function. In fact, it will be misleading to assume that technology is the same for different firms, as estimated coefficients of a common technology will be biased (Griliches, 1957). This has been recognized in the literature on localized technical change, which posits differential "drivers" of economic performance depending on the kind of technology used by a firm (Atkinson and Stigliz, 1969). Modeling and measuring localized technical change in this context involves first characterizing the different technologies, and then distinguishing the production patterns associated with these technologies and how they change over time.[ii]

In particular, the technological specification used for empirical analysis of production technologies and technical change should accommodate both different points on a production frontier and separate frontiers for different firms. Recognizing the presence of different output and input mixes and especially technologies may reduce apparent substitution elasticities, as substitution possibilities for a specific technology are likely more limited than implied by a single common production frontier that combines movements within and between production systems. It is also important to distinguish different technical patterns in terms of movements around versus between production frontiers, or changes in production systems, versus movements in the function itself, or technical change. That is, once different production systems or technological frontiers are recognized in the model, technical change involves an outward move at one point of the production function rather than a general shift of the function, or a shift in the technology-specific rather than common production frontier. Empirically analyzing productivity growth thus requires distinguishing different technical change patterns for the different production systems, including the rate of and input biases associated with technical change – differences in overall productivity growth and resulting input intensity.

One industry that has exhibited significant structural changes and production system differences in the past few decades, in both the U.S. and E.U. countries, is the dairy industry. To distinguish farms by their different technologies, researchers have sometimes categorized producers into, for example, organic versus conventional operations (e.g., Kumbhakar et al., 2009). However, such a grouping may be both arbitrary and incomplete. In this paper we instead use a latent class model (LCM) to group dairy producers into "classes" based on their probability of having a variety of characteristics that proxy different technologies

or production systems, called separating variables or q-variables. For example, for dairy operations, one might use characteristics such as cows/hectare or fodder/cow to proxy the use of pasture or purchased feed (extensive vs. intensive production) and labor/cow or capital/cow to proxy input intensity (associated with different milking practices). The latent class model allows us to represent a variety of classes (with the number of classes determined empirically), based on a combination of differences in such variables as well as netput (output and input) variables. The technological differences are then summarized in terms of the estimated parameters of the underlying multinomial logit (MNL) model for each class, the summary statistics by class, and the estimates of the technology by class. Further, the posterior probabilities show the extent to which the important technological differences are distinguished by the model.

Because the LCM model distinguishes the classes while simultaneously estimating their technological structures as different production frontiers, the classification of producers by technology depends on both the parameters of the MNL on which the probabilities are based and the parameters of the technological specification. We model the production structure for each class by a flexible transformation function model with multiple outputs and inputs to recognize farms' different netput intensities.

In summary, our model distinguishes the technological structure from the probability of being in a class, defined by a MNL model with multiple separating variables. The posterior probabilities distinguishing the classes and technology depending on the parameters of both the technology (transformation function) and the probability (MNL) model. Our technical change measures for the different technologies can thus be compared to consider the most productive technologies, changes in specific technologies, and movements between technologies. We find that overall (average) measures do not well reflect individual firms' production patterns if the technology of an industry is heterogeneous. That is, if there is more than one type of production frontier embodied in the data, it should be recognized that different firms may exhibit very different output or input intensities and changes associated with different production systems. In particular, in the context of localized technical change, firms with different technologies can be expected to show different technical change patterns, both in terms of overall magnitudes and associated relative output and input mix changes.

The Technological Model

For our purposes, a transformation function is desirable for modeling technological processes because multiple outputs are produced by Danish dairy farms (milk, livestock and crops), precluding estimation of the production technology by a production function, yet we wish to avoid the disadvantages of normalizing by one input or output as is required for a distance function. That is, imposing linear homogeneity on an input (output) distance function requires normalizing the inputs (outputs) by the input (output) appearing on the left hand side of the estimating equation. This raises issues not only about what variable should be chosen as the numeraire, but also about econometric endogeneity because the right hand side variables are expressed as ratios with respect to the left hand side variable. Although a common approach in input distance function-based agricultural studies is to normalize by land (e.g., Paul and Nehring, 2005), to express the function in input-per-acre terms, this is questionable when a key issue to be addressed is whether different kinds of farms with potentially different productivity use land more or less intensively.

We thus rely on a transformation function model representing the most output producible from a given input base and existing conditions, which also represents the feasible production set. This function in general form can be written as $0=F(\mathbf{Y},\mathbf{X},\mathbf{T})$, where $\mathbf{Y}$ is a vector of outputs, $\mathbf{X}$ is a vector of inputs, and $\mathbf{T}$ is a vector of (external) shift variables, which reflects the maximum amount of outputs producible from a given input vector and external conditions. By the implicit function theorem, if $F(\mathbf{Y},\mathbf{X},\mathbf{T})$ is continuously differentiable and has non-zero first derivatives with respect to one of its arguments, it may be specified (in explicit form) with that argument on the left hand side of the equation. Accordingly, we estimate the transformation function $Y_1= G(\mathbf{Y}_{-1},\mathbf{X},\mathbf{T})$, where, Y_1 is the primary output of dairy farms (milk) and $\mathbf{Y}_{-1}$ the vector of other outputs, to represent the technological relationships for the dairy farms in our data sample. Note that this specification does not reflect any endogeneity of output and input choices, but simply represents the technologically most Y_1 that can be produced given the levels of the other arguments of the F(•) function. We approximate the transformation function by a flexible functional form (second order approximation to the general function), to accommodate various interactions among the arguments of the function including non-constant returns to scale and technical change biases. A flexible functional form can be expressed in terms of logarithms (translog), levels (quadratic), or square roots (generalized linear, sometimes erroneously called generalized Leontief for a primal function). We use the generalized linear

functional form suggested by Diewert (1973) to avoid any mathematical transformations of the original data (e.g. taking logs of variables which would lead to modelling problems based on zero values).

$$(1)\ Y_{M,it} = F(Y_{NMQ,it}, \mathbf{X}_{it}, T)$$
$$= a_0 + 2a_{0NMQ}Y_{NMQ}^{0.5} + \sum 2a_{0k}X_k^{0.5} + a_{NMQNMQ}Y_{NMQ} + a_{kk}X_k + \sum a_{kl}X_k^{0.5}X_l^{0.5} + \sum a_{kNMQ}X_k^{0.5}Y_{NMQ}^{0.5}$$
$$+ b_T T + b_{TT}TT + \sum b_{kT}X_k^{0.5}T + b_{NMQT}Y_{NMQ}^{0.5}T,$$

for farm i in time period t, where $Y_1=Y_M$=total quantity of milk, $Y_2= Y_{NMQ}$=non-milk outputs is the only component of $\mathbf{Y}_{-1}$, $\mathbf{X}$ is a vector of X_k inputs X_{LD}=land, X_{LAB}=labor, X_{KAP}=capital, X_{COW}=cows, X_{FOD}= fodder, X_{EN}= energy, X_{CHM}=chemicals, and X_{VET}=veterinarian services, and a time trend T is the only component of the **T** vector.

When estimating the technology for a group of observations, if the firms (farms) in the sample are using different technologies estimating a "common" technological frontier is misleading. With a flexible functional form, even when assuming a common technology, differences among observations are at least partly accommodated because a different netput mix is allowed for in the production structure estimates that depend on all the other arguments of the function. For example, estimated output elasticities with respect to a particular input will depend on the levels of that input, all other inputs and current technical conditions, and so will differ by observation. Unobserved technological heterogeneity is also partially accommodated by a standard error term for econometric estimation, but then the factors underlying the heterogeneity cannot be directly represented and will bias parameter estimates if they are correlated with the explanatory variables (Griliches, 1957). To more fully recognize and evaluate heterogeneity among production systems, we thus explicitly distinguish technologies by estimating the technology separately for different groups or "classes" of farms. This is particularly important in order to explore technical change specific to a particular technology type. To group firms or farms with different technologies, researchers sometimes group their observations by exogenous classifications, such as farms that define themselves as "organic," or by a particular input threshold such as hectares per animal (to define a pasture-based or extensive operation). However, such divisions are at least somewhat arbitrary, and also usually rely on only one distinguishing factor. It seems preferable to group observations by their probability of exhibiting certain characteristics that differ among technologies, especially if multiple characteristics may distinguish production systems, as well as to estimate the groups and the technology in a one-step framework to allow for differences also in netput levels and mix. To accomplish this, we combine the estimation of our transformation function with a latent class structure (Greene, 2002, 2005), as explained further in the next section.

The Latent Class Model

Various methods to explicitly allow for heterogeneity in a production model have been used in the production literature. Some researchers have chosen their data sample based on some criterion of homogeneous production, such as Tauer and Belbase (1987) who delete farms in their sample with technologies too different from the norm[iii] and Felthoven et al. (2009) who focus on a portion of a fishing fleet with specific characteristics (catcher-processors). Some have chosen particular characteristic to divide the sample and estimate different frontiers, such as Hoch (1962) who separates Minnesota dairy farms by location, Bravo-Ureta (1986) who separates new England dairy farms based on breed, Newman and Matthews (2006) and Tauer (1998) who separate Irish and New York dairy farms by production process (stanchion versus parlor milking and specialist and non-specialist farms, respectively), and Kumbhakar et al. (2009) and Gillespie et al. (2009) who separate Finnish and U.S. dairy farms, respectively, into conventional and organic farms. Researchers such as Maudos et al. (2002) and Alvarez et al. (2008) instead accommodate multiple criteria for separating farms using cluster analysis based on output and input ratios, which divides the sample according to similarities in specific characteristics by maximizing the variance between groups and minimizing the variance within groups. Further, studies such as Kalirajan and Obwona (1994), Huang (2004), and Greene (2005) rely on random coefficient models that essentially model each farm as a separate technology in the form of continuous parameter variation.

It has increasingly been recognized, however, particularly in the stochastic frontier (technical inefficiency) context that is the focus of most of these studies, that latent class models are desirable for representing heterogeneity (Greene, 2002, 2005, Orea and Kumbhakar, 2004). This approach separates the data into multiple technological "classes" according to estimated probabilities of class membership based on multiple specified characteristics. Each firm/farm can then be assigned to a specific class based on the probabilities. This method distinguishes the classes based on homogeneity among firms/farms in

terms of both the estimated technological and probability (multinominal logit, MNL) relationships, rather than looking for similarity in specific variables. The LCM model estimates a MNL model in one stage with the estimation of the overall technological structure (although the number of parameters that may be estimated simultaneously by LIMDEP is limited by degrees of freedom for multiple output/input specifications). Statistical tests can be done to choose the number of classes or technologies that should be distinguished. A random effects model assuming firm-specific random terms along with the technological groupings can be incorporated to further capture firm heterogeneity, as developed by Greene (2005) and Cameron and Trivedi (2005) and applied by Abdulai and Tietje (2007) for stochastic frontier analysis of German dairy farms and Alvarez and del Corral (2009) for Spanish dairy farms. For our analysis we focus on the technological structure and technical change rather than on unobserved "inefficiency," so we do not include a one-sided error as in a stochastic frontier model. Our specification of multiple technologies based on multiple characteristics, outputs and inputs, along with random effects and a flexible functional form, however, accommodate heterogeneity in our sample of Danish dairy farms.

More specifically, we can write our latent class model in general form as equation (1) for class j:

(2) $Y_{M,it} = F(Y_{NMQ,it}, \mathbf{X}_{it}, T)\,|_j$

where j denotes the class or group containing farm i and the vertical bar means a different function for each class j. As we are assuming that the error term for this function is normally distributed, the likelihood function for farm i at time t for group j, LF_{ijt}, has the standard OLS form. In addition, as in Greene (2005), the unconditional likelihood function for farm i in group j, LF_{ij}, is the product of the likelihood functions in each period t, and the likelihood function for each farm, LFi, is the weighted sum of the likelihood functions for each group j (with the prior probabilities of class j membership as the weights): $LF_i = \Sigma j\, P_{ij}\, LF_{ij}$ The prior probabilities P_{ij} must, by definition, fall between zero and one and sum to one for each farm. They are therefore typically parameterized as a multinomial logit (MNL) model, based on the farm-specific characteristics used to distinguish the technologies or determine the probabilities of class membership, called separating- or q-variables (q_i), and the parameters of the MNL to be estimated for each class (relative to one group chosen as numeraire), δ_j. That is,

(3) $P_{ij} = \exp(\delta_j q_i)/[\Sigma_j \exp(\delta_j q_i)]$, or,

(4) $P_{ij}=\exp(\delta_{0j} + \Sigma_n\, \delta_{nj}\, q_{nit})/[\Sigma_j \exp(\delta_{0j} + \Sigma_n\, \delta_{nj}\, q_{nit})]$,

where the q_{nit} are the N q-variables for farm i in time period t. For our application we include four types of features that are key to distinguishing technologies and may be represented by alternative ratios.[iv] One important feature of dairy farms is the intensive or extensive nature of production, which may be reflected by pasture versus purchased feed; two variables that could capture this are thus $q_{COW,HA}$=cows/hectare and $q_{FOD,COW}$=fodder/cow. The extent of organic production may be captured by $q_{CHM,HA}$=chemicals/hectare or $q_{ORG,TOT}$= organic milk revenue/total revenue.[v] The input intensity of production may be represented by q_{LABCOW}=labor/cow or $q_{KAP,COW}$=capital/cow.[vi] Finally, production diversity or specialization is reflected in the ratio of outputs, $q_{M,TOT}$=milk/total output. These separating variables are specific technological indicators distinguishing farms with different technologies. We chose our preferred q-variables by trying different combinations of the four types of indicators and evaluating the latent class model (LCM) q-variable coefficient's estimates' significance and the resulting posterior probabilities for the individual classes. The number of classes is determined by AIC/SBIC tests suggested by Greene (2002, 2005) that "test down" to show whether fewer classes are statistically supported. Further, the base model incorporates a panel data specification where each farm is recognized as a separate entity that is assigned to a particular class.

(5) $y_{M,it}\,|_j = a_0 + 2a_{0NMQ,j}\, y_{NMQ,it}^{0.5} + \sum 2a_{0k,j}\, x_{k,it}^{0.5} + a_{NMQNMQ,j}\, y_{NMQ,it} + a_{kk,j}\, x_{k,it} + \sum a_{kl,j} x_{k,it}^{0.5} x_{l.it}^{0.5} + \sum a_{kNMQ,j}\, x_{k,it}^{0.5}\, y_{NMQ,it}^{0.5} + b_{T,j}\, t_{it} + b_{TT,j}\, t_{it} t_{it} + \sum b_{kT,j}\, x_{k,it}^{0.5}\, t_{it} + b_{NMQT,j}\, y_{NMQ,it}^{0.5}\, t_{it} + e_{it}\,|_j$,

for farm i in time period t and class j, with e denoting an iid standard error term and the indezes as explained above. However, as an alternative specification we allow each observation to be a separate entity, allowing farms to switch between classes to identify changes in production systems over time (i.e. a cross-sectional specification):

(6) $y_{M,i}\,|_j = a_0 + 2a_{0NMQ,j}\, y_{NMQ,i}^{0.5} + \sum 2a_{0k,j}\, x_{k,i}^{0.5} + a_{NMQNMQ,j}\, y_{NMQ,i} + a_{kk,j}\, x_{k,i} + \sum a_{kl,j} x_{k,i}^{0.5} x_{l.i}^{0.5} + \sum a_{kNMQ,j}\, x_{k,i}^{0.5}\, y_{NMQ,i}^{0.5} + b_{T,j}\, t_i + b_{TT,j}\, t_i t_i + \sum b_{kT,j}\, x_{k,i}^{0.5}\, t_i + b_{NMQT,j}\, y_{NMQ,i}^{0.5}\, t_i + e_i\,|_j$,

for observation i and class j, with e and the indezes as explained above.

The probabilities P_{ij} are therefore functions of the parameters of the MNL model, and the likelihoods LF_{ij} are functions of the parameters of the technology for class j farms, so the likelihood function for firm i

is a function of both these sets of parameters. The overall log-likelihood function for our model, defined as the sum of the individual log-likelihood functions LF_i, can be maximized using standard econometric methods. Further, the posterior probabilities of class members can be computed from the resulting parameter estimates using Bayes Theorem:

(7) $P(j/i) = P_{ij}LF_{ij}/\Sigma j\ P_{ij}LF_{ij}$.

The posterior probabilities thus also depend on both the parameters of the technology (arguments of L_{ij}), and the parameters of the MNL model (arguments of P_{ij}). As noted by Orea and Kumbhakar (2004), this means that the LCM model can group the firms/farms into classes based on goodness of fit of the technological frontier even if other "sample-separating' information (q-variables) is not provided.

For purposes of our analysis, due to degree of freedom problems for the LCM model from the many outputs and inputs in our data, we initially characterize our classes based on an approximation to the GL transformation function that does not include cross-effects. This is equivalent to using a Cobb-Douglas function – it is essentially a first-order approximation allowing for appropriate curvature of the overall marginal product and transformation curves for each input and output but not for second-order interaction terms among these variables. The resulting first-order elasticities represent the contributions of each output and input to production, as well as overall technical change and returns to scale, for each class. To accommodate and measure the second order effects involving output and input technical change biases and substitution, we then estimate the full GL form for the full sample and the separate classes. If the distinctions among classes capture key differences in technology, the average first-order elasticities for the constrained and fully flexible functional forms will be comparable, but incorporating the interaction terms will allow assessment of cross effects.

The Measures

More specifically, to represent and evaluate the technological or production structure, the primary measures we wish to compute are first- and second-order elasticities of the transformation function. The first-order elasticities of the transformation function in terms of milk output Y_M represent the (proportional) shape of the production possibility frontier (given inputs) for output Y_{NMQ}, and the shape of the production function (given other inputs and Y_{NMQ}) for input X_k – or output trade-offs and input contributions to milk output respectively. That is, the estimated output elasticity with respect to the "other" (non-milk) output, $\varepsilon_{M,NMQ}=\partial \ln Y_M/\partial \ln Y_{NMQ}= \partial Y_M/\partial Y_{NMQ}\bullet(Y_{NMQ}/Y_M)$, would be expected to be negative as it reflects the slope of the production possibility frontier, with its magnitude capturing the (proportional) marginal trade-off. The estimated output elasticity with respect to input k, $\varepsilon_{M,k}=\partial \ln Y_M/\partial \ln X_k= \partial Y_M/\partial X_k\bullet(X_k/Y_M)$, would be expected to be positive, with its magnitude representing the (proportional) marginal productivity of X_k.

Second-order own-elasticities may also be computed to confirm that the curvature of these functions satisfies regularity conditions; the marginal productivity would be expected to be increasing at a decreasing rate, and the output trade-off decreasing at an increasing rate, so second derivatives with respect to both Y_{NMQ} and X_k would be negative (concavity with respect to both outputs and inputs). Returns to scale may be computed as a combination of the Y_M elasticities with respect to the non-milk output(s) and inputs. For example, for a production function returns to scale is defined as the sum of the input elasticities to reflect in a sense the distance between isoquants. Similarly for a transformation function such a measure must control for the other output(s). Formally, returns to scale are defined for the transformation function similarly to the treatment for the distance function in Caves, Christensen and Diewert (1982) – for our purposes as $\varepsilon_{M,X}=\Sigma_k\ \varepsilon_{M,k}/(1 - \varepsilon_{M,NMQ})$.[vii] Technical change is measured by shifts in the overall production frontier over time. As our only technical change variable is the trend term T, productivity/technical change is estimated as the output elasticity with respect to T, $\varepsilon_{M,T}=\partial \ln Y_M/\partial T= \partial Y_M/\partial T\bullet(1/Y_M)$. This represents how much more milk may be produced on an annual basis in proportional terms, given the levels of the inputs and other output(s).

These measures may be computed for each observation and presented as an average over a subset of observations (such as for the full sample, a farm, a time period or a particular class), or may be computed for the average values of the data for a subset of observations. The latter approach is called the delta method; it evaluates the elasticities at one point that represents the average value of the elasticity for a particular set of observations, allowing standard errors to be computed for inference even though the elasticity computation involves a combination of econometric estimates and data[viii,ix] In addition to computing technical change in terms of relative *shifts* in production frontiers, we can compute the relative

levels of productivity among different groups or classes. This requires determining whether one frontier is above the other, in terms of predicted output levels for a given amount of inputs, as in Kumbhakar et al. (2009) and Alvarez and del Corral (2009). Further, we can compute second order or cross elasticities to evaluate output and input substitution as well as output and input-using or -saving technical change (technical change biases) if a flexible functional form is estimated. These elasticities involve second-order derivatives such as, for input substitution, $\varepsilon_{k,l} = \partial^2 Y_M/\partial X_k \partial X_l \bullet [X_l/(\partial Y_M/\partial X_k)]$. If one thinks of $MP_{M,k}=\partial Y_M/\partial X_k$ as the marginal product of Y_M with respect to X_k (holding all other arguments of the function, including Y_{NMQ}, constant), this elasticity can be written as $\varepsilon_{k,l} = \partial MP_{M,k}/\partial X_l \bullet (X_l/MP_{M,k})$. Such an elasticity represents the extent to which the marginal product of X_k changes when X_l changes, or substitutability among the inputs. Similarly, for technical change, $\varepsilon_{k,T} = \partial^2 Y_M/\partial X_k \partial T \bullet [1/(\partial Y_M/\partial X_k)] = \partial MP_{M,k}/\partial T \bullet (1/MP_{M,k})$ represents whether technical change is input k-using or -saving – or tends to increase or decrease the input-intensity of input k – as $\varepsilon_{K,T}$ is positive or negative. We can also measure whether returns to scale is increasing or decreasing over time (with technical change) for each class by computing $\varepsilon_{Y,X,T}= \partial \varepsilon_{Y,X}/\partial T$.

The Data

The data used for our illustration are for milk (total and organic) and non-milk outputs, and land, labor, capital, cow, fodder, energy, veterinary and chemicals inputs, as well as deflators (producer price indexes for milk and dairy products, agricultural materials, and machinery and buildings). The data are taken from Landscentret, Denmark ("Regnskabsdatabase": economic farm account database collected for various years) and Danmark Statistic (various agricultural price indezes). Summary statistics for the data by the final preferred (3) classes can be obtained from the authors upon request due to space limitations. Overall, milk was about two-thirds of total production for these farms, which averaged about 77 hectares with about 68 cows, 4300 labor hours/year, 6.2 million Danish Kronor in capital, and about 5600 Kronor in feed/cow/year, with revenue of about 1,800,000 Kronor/year (in 1986 monetary units). When divided into classes, Class 1 farms tend to be larger operations with about 2,500,000 Kroner/year in revenue, more cows and land (about 93 cows and 109 hectares), less labor and more capital input per cow, and more organic production and fodder/cow on average – although the range for all of the variables is very large. Class 3 is the reverse – seemingly more traditional farms that are smaller, somewhat more diversified, with more labor and less land, capital and fodder per cow. Class 2 is in the middle in terms of size, with the least milk/total revenue (more diversification) and organic/total production. Differences over time for the data for the first and last years of the sample show a dramatic increase in milk production per farm (nearly three-fold) and proportion of organic milk while non-milk output was dropping, combined with much more capital and land, less chemicals use, more than twice as many cows, and less labor and fodder per cow. These trends are consistent with those for dairy farms in the U.S. and other EU countries toward larger more specialized farms and more capital-intensive production systems.

The Results

We estimated our LCM model by Maximum Likelihood (ML) methods using LIMDEP 9.0. As noted, our base LCM model includes all first order and own second order terms, to allow for appropriate curvature of the function, but it does not include any cross-terms between outputs and inputs as there were too many parameters to distinguish classes with the fully flexible general linear model in LIMDEP (i.e. insufficient degrees of freedom). The overall first-order elasticities representing output and input composition and technical change would be expected, however, to be well approximated by such estimates (as we will see below), so the fundamental characteristics of the different farms will be taken into account for the separation of the farms into classes. The parameter estimates for this model can be obtained from the authors upon request due to space limitations. As discussed above, the measures of interest for our analysis are, however, computed as combinations of these parameters rather than based directly on the estimated coefficients. The first measures to evaluate are thus the elasticity measures for the full data sample. As discussed above, these first order output (milk, Y_M) elasticity estimates for our constrained (no cross-terms) model reflect output tradeoffs, input contributions, returns to scale and technical change, evaluated at the mean values of the variables for all farms in our data.

The (proportional) tradeoffs between the outputs are given by the $\varepsilon_{M,NMQ}$ elasticity, where M denotes Y_M and NMQ denotes Y_{NMQ}. The estimate for this elasticity of approximately -0.17 shows that producing one percent more milk, given input use, on average requires reducing other outputs by about 17 percent for

the farms in our data. The (proportional) productive contributions of the inputs are given by the $\varepsilon_{M,k}$ elasticities (k= LD, LAB, KAP, COW, FOD, EN, VET, CHM). These output elasticities with respect to the inputs, which can be interpreted similarly to more familiar Cobb-Douglas production function coefficient estimates, show that the livestock input (X_{COW}) comprises the largest marginal input "share" or contribution to output at about 50 percent, fodder is about 21 percent, capital is next at about 16 percent, and land and veterinary care follow at about 12-13 percent. Labor has a small productive contribution of about 6 percent and chemicals and energy even less at about 2 percent. In combination, these estimates result in a slightly increasing returns to scale ($\varepsilon_{Y,X}$) estimate of 1.04; a one percent increase in all netputs generates an increase in milk production of about 1.04 percent.

In turn, our technical change measure reflects changes in potential output (milk) production over time holding input use and non-milk production constant, is statistically as well as economically significant at about 0.013; output per unit of input has increased about 1.3 percent per year on average for the farms in our sample. Note also that the reported second order own-elasticity estimates confirm the appropriate curvature on the relationships represented by our first order output elasticities; as non-milk production Y_{NMQ} increases the opportunity cost in terms of milk production increases on the margin, and the (proportional) marginal products of all inputs are (positive but) diminishing. The rate of technical change is also decreasing over time. A fundamental premise of our study, however, is that such overall (average) measures do not well reflect individual firms'/farms' production patterns if the technology is heterogeneous. That is, if there is more than one type of production frontier embodied in the data, it should be recognized that different farms may exhibit very different output or input intensities and changes associated with different production systems. In particular, in the context of localized technical change, farms with different technologies would be expected to have different technical change patterns, both in terms of overall magnitudes and associated relative output and input mix changes.

To distinguish and evaluate such technologies and associated technical change, we need to specify the q- or separating-variables underlying the different technologies, and determine the number of different technologies or classes in which to group our data. For the first of these problems, we used different combinations of possible variables reflecting four distinctions among farm technologies we believe to be important for dairy farms – extensive/intensive, organic/conventional, input (labor and capital) intensity, and diversification/specialization. Although the models using different subsets of these potential q-variables are not nested and thus cannot be directly tested, we evaluated their relevance based on the significance of the resulting MNL coefficient (ε_{nj}) estimates. These experiments suggested that the most relevant grouping was $q_{FOD,COW}$=fodder/cow, $q_{ORG,TOT}$= organic revenue/total revenue, $q_{LAB,COW}$=labor/cow and $q_{M,TOT}$=milk/total output. The δ_o and δ_n estimates for this q-variable specification based on two, three, and four classes in the LCM model are presented in Table A1. All of the constant terms for the 2 and 3 class models are statistically significant at the 1 percent level, suggesting that even without the q-variables the different farm production factors show significantly distinct technologies. However, the q-variables identify additional distinguishing or separating characteristics.

A key distinguishing factor among these farms – in terms of statistical significance holding other production factors constant – appears to be their diversity versus specialization (the amount of milk relative to total output), although the average summary statistics did not appear that different. For the two class specification, the farms in Class I (with prior probability of 80 percent being in that class) appear more specialized (with a positive and significant $\varepsilon_{M/TOT}$ coefficient) than those in Class 2. When three classes are distinguished, Class 3 becomes the base class with the highest prior probability, and farms in other classes have a lower milk share – especially Class 2, as was evident from the summary statistics. Farms in both Class 1 and Class 2 also use less labor/cow than those in Class 3, and those in Class 1 also sell relatively more organic milk and in Class 2 (with a less than 10 percent prior probability of being in this class) purchase less fodder/cow, consistent with the summary statistics. When four classes are distinguished, the significance of the q-variables is somewhat lower overall (than for the 3-class case), but farms in Classes 1-3 still have a significantly lower milk share relative to the base (and largest prior probability) class, while those in Class 1 also have more organic production and labor intensity, and in Class 3 have greater labor intensity. In this case fodder/cow seems not to be as significant a separating variable, perhaps as it is instead captured in a combination of the other q-variables when this many combinations are allowed for.

To determine how many classes are statistically supported, it is now recognized in the literature that one should "test down" from the most classes to determine whether restricting classes is justified by statistical tests. Although likelihood ratio tests may be used, Greene (2005) showed that it is preferable to use AIC and SBIC tests – in this case to test down from four classes. Such tests showed for our specification that three classes were statistically supported but two classes were not. Also note that the prior probabilities for our preferred three class model are about 0.39. 0.08 and 0.54 for classes 1-3 but the average posterior probabilities for the farms *within* each of these classes are about 0.99, 0.97 and 0.98 (for the 110, 74 and 120 farms in those categories), respectively, indicating a very good "fit" for our classification scheme. Given the division of classes into three groups based on the chosen q-variables and first order technological specification, the next step is representing the full production technology for the separate classes. First, however, it is important to consider whether the base production structure (transformation function) model without cross-effects, used for separating the classes, reflects the primary characteristics of the overall production technology.

To evaluate the desirability of including additional cross-terms, as well as the appropriateness of using the base constrained (first order) model for distinguishing the classes, we estimated a fully flexible version of equation (1) for comparison. The parameter estimates for this model can be obtained from the authors upon request due to space limitations. Tests of the joint significance of the cross-effects relative to constraining them to zero showed that a fully flexible form is statistically supported. Tests for setting subsets of cross-terms, including all input-cross terms, all T-cross terms, and all Y_{NMQ}-X_k cross-terms, to zero also showed the joint significance of these cross-effects. For our full analysis of the production structure, therefore, we wish to use the fully flexible model. As already noted, the fact that the LIMDEP LCM algorithm does not have enough degrees of freedom to estimate the fully flexible model for the classes precludes using such a model for the first step. However, the validity of using the base model for distinguishing classes, but the flexible model for evaluating the full production structure for the classes, may be inferred by comparing the elasticities for the constrained and unconstrained model to determine whether they reflect sufficiently similar overall average contributions of the outputs and inputs. Comparing these elasticity estimates shows that, although the cross-terms will provide us with additional insights about underlying relationships, the overall patterns are effectively captured by the constrained model. On balance, therefore, the use of the constrained model to do the initial division into classes seems justifiable, particularly as the heterogeneity of the farms in terms of their output mix is taken into account in the division into classes by including the $q_{M,TOT}$ q-variable, and can be explored more completely with the fully flexible model. That is, first consider the different productivity levels implied by the different production technologies. One way to consider whether different technologies are more or less productive is to evaluate the fitted output levels (milk quantity – left hand side variable) for the data for the different classes based on the parameters of the other classes (Kumbhakar et al., 2009, Alvarez and del Corral, 2009). To pursue this, we used the average data for the variables for each class, as reported in Table 1.

Table 1: Fitted Productivity Levels, average data for different groups

sample technology	full sample	class 1 sample	class 2 sample	class 3 sample
1st class	497.19	**717.31**	459.62	354.59
2nd class	403.03	540.29	**381.60**	301.86
3rd class	483.22	643.77	387.49	**316.02**

For example, for the average data for the full sample, the fitted value of Y_M is highest for farms in Class 1 and lowest for those in Class 2, suggesting that the Class 1 technology is generally the most productive. The fitted values for the different classes support this conclusion; for example, the fitted values for Class 1 farms using their own estimated technological parameters is 717.31, but using those for the other classes is lower and for Class 2 is the lowest. For the data for the other classes, in reverse, using the Class 1 parameters gives a higher fitted output level than using the parameters for their own class. This roughly confirms the notion from our discussion of the descriptive statistics and q-variable parameters that Class 1 farms are more efficient.[x,xi] Next consider the first order and own second order elasticities for the separate classes and the fully flexible model, presented in Table A2, which represent the production characteristics of each technology. Note that, as the first order elasticities reflect each output's and input's marginal product weighted "share" (e.g., $\varepsilon_{M,k}=[(\partial Y_M/\partial X_k)\bullet X_k]/Y_M$), high values of these elasticities may arise either from a large marginal product or a large amount of input X_k. Note also that the primary interpretation of

the second order elasticities is in terms of curvature; all the estimates are negative, consistent with the concavity requirements of the transformation function.

The first order elasticities for non-milk outputs for all classes are negative, as they should be, and the larger (in absolute value) estimate for Class 1 suggests that with that technology an increase in milk production on the margin involves more decrease in other outputs. This is consistent with the summary statistics that suggest milk relative to non-milk output is higher for these farms, even though the average $q_{M,TOT}$ ratios are not very different than those for Class 3. The marginal contributions of cows, and especially land and chemicals are larger for Class 1 than the other classes. This appears consistent with high marginal products for each of these inputs, as their levels are comparable (relative to milk production) or lower (for chemicals) for this class relative to the other classes, again suggesting that these farms are somewhat more efficient than those in Classes 2 and 3. In reverse, the marginal contribution of capital is higher for Classes 2 and 3, suggesting that more capital investment might enhance productivity. Further, for Class 2 the marginal contribution of labor is higher and for fodder is lower than for the other classes. In turn, returns to scale are essentially constant for Class 3, even though they are somewhat smaller farms, suggesting that the production systems of these farms must be adapted to take advantage of returns to scale as they grow – for example to become more capital and less labor intensive. Increasing returns to scale are evident for the other two technologies – especially for Class 2. Note that the overall returns to scale estimate for the GL model, therefore, overestimates returns to scale for Class 1 and especially Class 3 farms, and underestimates it for Class 2 farms.

Further, technical progress is evident for all the technologies, but the most for the farms in Class 1; output given non-milk production and input use is growing at about three percent per year for farms in Class 1 and roughly half that for the other two kinds of farms. It is also increasing at a decreasing rate, as is evident from the second order elasticity, but at similar rates for all classes. The overall technical change measure for the full sample and GL model therefore under-estimates technical change for Class 1 but over-estimates it for the other classes. Further, without the cross terms the measure under-estimates technical change for *all* classes relative to the fully flexible model and class distinctions.

The fully flexible model also provides insights about the input- and output-specific patterns of technical change, which underlie the overall technical change elasticity reflecting how much milk production per unit of input (or given input use) has increased over time. This can be seen from the cross elasticities for the full sample. The elasticities of $\varepsilon_{M,NMQ}$ and each $\varepsilon_{M,k}$ elasticity with respect to T are primarily significant. These elasticities show that on average for the full sample milk production growth over time has been associated with: (i) a greater trade-off between milk and non-milk production (consistent with a trend toward more specialization) ; (ii) a slightly greater marginal contribution of land (while land has been increasing slightly faster on average than cows, (iii) greater marginal contributions of both labor and capital (while labor and capital use per cow have been falling and rising, respectively); (iv) a smaller marginal contribution of cows (as cows per farm has expanded); (v) a greater marginal contribution of fodder while fodder purchases have not increased on average as much as cows; (vi) a smaller contribution of energy (with no apparent underlying intuition but it is a small proportion); and (vii) essentially the same contributions of chemical and vet use (while chemical use per hectare has been decreasing substantially and vet services per cow have stayed approximately stable). Note also that returns to scale have been increasing over time even while farm size has been increasing.

When these elasticities are presented for the different classes, in Table A2, it is clear that different technical change patterns are occurring for the different technologies. In particular, for Class 1 the marginal contribution of labor is larger and of capital is smaller and less significant – apparently due to a larger marginal product of labor with its lower levels and a marginal product of capital that has fallen somewhat with higher capital levels. Returns to scale are also increasing even faster than on average, even though these farms tend to be the largest farms. By contrast, both the marginal contributions of labor and capital are smaller for both other classes (although that for capital is statistically significant for Class 2). The changes in the contributions of land and cows are also smaller but generally insignificant, and the rising returns to scale over time evident for Class 1 farms is less so for Class 2 and negligible for Class 3. In reverse, the marginal contribution of chemicals is significantly increasing for Class 2, which is the class with the smallest share of organic milk production.

Another question about technical change is the extent to which (and which) farms switch between classes (move to different production systems) or exit the industry. Our "preferred" estimates with random

effects for each farm and based on a panel data specification, however, group the observations into class by farm rather than by observation, precluding consideration of such changes. To address this question we thus must categorize the observations rather than the farms into classes. This model is not nested and thus not directly comparable to the random effects farm-based specification, and in fact would be expected to yield biased estimates without the panel related random effects. Estimating the model allows us, however, to generally consider whether the results are comparable and assess farm switching and exit patterns. Although exploring such a model in detail is beyond the scope of this paper, note that the classification into categories by observation is roughly consistent with the farm random effects model. 1099 of the observations fell into Class 1, 693 into Class 2, and 1396 into Class 3. Class 1 again contained the largest, most specialized and most organic-oriented farms – even larger in terms of land and cows than for the farm model (which might be expected as the industry was evolving toward such a farm structure). Class 2 observations were again the least specialized farms, in between Class 1 and 3 in size, with the most labor and fodder per cow. In terms of switches, 344 farms moved from Class 3 into other classes – 226 of them to Class 1 – over the time period. 172 farms moved from Class 2, but most of these moved to Class 3 (165) rather than Class 1. The majority of the farms that switched away from Class 1 also moved to Class 3 – 91 of the 106 in this category. There is therefore a general trend from Classes 2 to 3 and 3 to 1, as would be expected by their measured productivities. Note also that 26 of the 30 farms that exited the industry were categorized as Class 2 farms in their last year by this model; the remaining four included one in Class 1 and three in Class 3. However, the farm classifications were nearly evenly divided among the different classes in the random effects farm model, suggesting that farms that became less productive over time tended to transition into Class 2 farms before they left the industry. Thus, the categorization of farms into classes over 20 years could be misleading in terms of which will exit the industry, as they may initially have been relatively productive farms that fell behind over time.

Finally, we can consider general substitutability patterns from the estimated cross-elasticities (these estimates can be obtained from the authors upon request). Overall, the cross-terms that reflect substitutability among inputs are largely significant. For the full sample, interesting patterns found are that more non-milk production is associated with a higher contribution of labor and lower contribution of fodder, as one would expect for more pasture-based farms. More land and more fodder imply a greater, but more labor and cows a lower, contribution of chemicals – perhaps as the marginal product of chemicals is larger for larger farms. Further, more capital is associated with greater contributions of both cows and fodder, consistent with trends toward larger farms with more intensive production. When the sample is broken down into classes these patterns are quite different. For example, more non-milk production is not associated with labor contribution for any class, and only implies a lower fodder contribution for Class 1. It is, however, associated with a greater marginal contribution of cows for Class 3, and of chemicals for both Class 2 and Class 3. More cows are also associated with a greater contribution of chemicals for Class 2 but both more cows and more land imply a lower contribution of chemicals for Class 3, while there is very little association of any other netput with chemicals use for Class 1. Distinguishing the technologies thus appears very important for representing substitutability, but seems to imply *different* substitutability rather than *lower* overall substitutability.

Concluding Remarks

The main finding of our study is that overall (average) measures do not well reflect individual firms' production patterns if the technology of an industry is heterogeneous. That is, if there is more than one type of production frontier embodied in the data, it should be recognized that different firms may exhibit very different output or input intensities and changes associated with different production systems. In particular, in the context of localized technical change, firms with different technologies can be expected to show different technical change patterns, both in terms of overall magnitudes and associated relative output and input mix changes. Assuming a uniform homogenous technology would result in inefficient policy recommendations leading to suboptimal industry outcomes. This seems to be especially relevant for environmentally motivated policy measures aiming to support less intensive production systems. Future research should consider localized technical change using more specific measures of technical change. This could be done by direct measures related to learning by doing and/or geographical proximity both as arguments of the technology function as well as potential factors for a deviation from the relevant technological frontier.

References

Abdulai, A. and H. Tietje. 2007. "Estimating Technical Efficiency under Unobserved Heterogeneity with Stochastic Frontier Models: Application to Northern German Dairy Farms." *European Review of Agricultural Economics* 34: 393-416.

Alvarez, A., J. del Corral, D. Solis, and J.A. Perez, "Does Intensification Improve the Economic Efficiency of Dairy Farms?" *Journal of Dairy Science* 91:3693-3698.

Alvarez, A. and J. del Corral. 2009. "Identifying Different Technologies Within a Sample Using a Latent Class Model: Extensive Versus Intensive Dairy Farms." Forthcoming, *European Review of Agricultural Economics*.

Alvarez, A., J. del Corral, and L.W. Tauer. 2009. "Detecting Technological Heterogeneity in New York Dairy Farms." Cornell University Working Paper.

Antonelli C. 1995. *The Economics of Localized Technological Change and Industrial Dynamics*. Dordrecht:Kluwer.

Atkinson, B.A. and J. Stiglitz. 1969. "A New View of Technological Change. " *The Economic Journal* 79:573-578.

Battese, G., P. Rao, and C. O'Donnell. 2004. "A Metafrontier Production Function for Estimation of Technical Efficiencies and Technology Gaps for Firms Operating under Different Technologies." *Journal of Productivity Analysis* 21: 91-103.

Cameron, C. and P.K. Trivedi. 2005. *Microeconometrics: Methods and Applications*. Cambridge University Press, New York.

Caves, D.W., L.R. Christensen and W.E. Diewert. 1982. "The Economic Theory of Index Numbers and the Measurement of Input, Output and Productivity." *Econometrica* 50:1393-1414.

Diewert, W.E., 1973. "Functional Forms for Profit and Transformation Functions." *Journal of Economic Theory* 6:284-316.

Felthoven, R.G., M. Torres and C.J.M Paul. 2009. "Measuring Productivity Change and its Components for Fisheries: The Case of the Alaskan Pollock Fishery, 1994-2003" *Natural Resource Modeling* 22(1):105-136.

Gallant, A.R. and A. Holly. 1980. "Statistical Inference in an Implicit, Nonlinear, Simultaneous Equation Model in the Context of Maximum Likelihood Estimation." *Econometrica* 48:697–720.

Gillespie, J., R. Nehring, C. Hallahan, C. J. Morrison Paul and C. Sandretto, 2009. "Economics and Productivity of Organic versus Non-organic Dairy Farms in the United States." Manuscript, ERS/USDA.

Greene, W. 2002. "Alternative Panel Data Estimators for Stochastic Frontier Models." Working Paper, Department of Economics, Stern School of Business, NYU.

Greene, W. 2005. "Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model." *Journal of Econometrics* 126(2):269-303.

Griliches, Z. 1957. "Specification Bias in Estimates of Production Functions." *Journal of Farm Economic*s 49:8-20.

Hoch, I. 1962. "Estimation of Production Function Parameters Combining Time-Series and Cross-Section Data." *Econometrica* 30: 34-53.

Huang, H. 2004. "Estimation of Technical Inefficiencies with Heterogeneous Technologies." *Journal of Productivity Analysis* 21: 277-296.

Kalirajan, K.P. and M.B. Obwona. 1994. "Frontier Production Function: The Stochastic Coefficients Approach." *Oxford Bulletin of Economics and Statistics* 56: 87-96.

Kumbhakar, S., E. Tsionas and T. Sipiläinen. 2009. "Joint Estimation of Technology Choice and Technical Efficiency: an Application to Organic and Conventional Dairy Farming." Forthcoming, *Journal of Productivity Analysis*.

Maudos, J., J. Pastor, and F. Pérez. 2002. "Competition and Efficiency in the Spanish Banking Sector: the Importance of Specialization.: *Applied Financial Economics* 12: 505-516.

Newman, C. and A. Matthews. 2006. "The Productivity Performance of Irish Dairy Farms 1984-2000: a Multiple Output Distance Function Approach." *Journal of Productivity Analysis* 26: 191-205.

Nicholson, W., and C. Snyder. 2008. "Microeconomic Theory." 10th ed., Thomson South-Western Publishers, Ohio.

Oehlert, G.W. 1992. "A Note on the Delta Method." *American Statistician* 46:27-29.

Orea, L. and S.C. Kumbhakar. 2004. "Efficiency Measurement Using a Latent Class Stochastic Frontier Model." *Empirical Economics*. 29:169-183

Paul, C.J.M. and R. Nehring. 2005. "Product Diversification, Production Systems, and Economic Performance in U.S. Agricultural Production." *Journal of Econometrics* 126:525-548

Tauer, L.W., and K. Belbase. 1987. "Technical Efficiency of New York Dairy Farms." *Northeastern Journal of Agricultural and Resource Economics* 16:10-16.

Tauer, L.W., 1998. "Cost of Production for Stanchion versus Parlor Milking in New York." *Journal of Dairy Science* 81:567-569.

Appendix Table A1: Q-Variable Coefficients for Technology Classes

Two Classes			*Three Classes*			*Four Classes*			*Prior Class Probabilities*			
class 1	estimate	t-stat	class 1	estimate	t-stat	class 1	estimate	t-stat	Class 1	Class 2	Class 3	Class 4
δ_0	-5.250	*-2.50*	δ_0	4.851	*2.60*	δ_0	2.184	*1.88*		*Two Class Model*		
$\delta_{FOD/COW}$	-0.034	*-0.35*	$\delta_{FOD/COW}$	0.049	*0.66*	$\delta_{FOD/COW}$	-0.046	*-0.38*	0.800	0.197		
$\delta_{ORG/TOT}$	-0.478	*-0.55*	$\delta_{ORG/TOT}$	2.434	*3.16*	$\delta_{ORG/TOT}$	1.280	*1.78*		*Three Class Model*		
$\delta_{LAB/COW}$	8.319	*0.80*	$\delta_{LAB/COW}$	-32.173	*-3.79*	$\delta_{LAB/COW}$	-34.710	*-2.80*	0.388	0.077	0.535	
$\delta_{MLK/TOT}$	25.370	*3.65*	$\delta_{MLK/TOT}$	-13.445	*-2.12*	$\delta_{MLK/TOT}$	-13.824	*-2.75*		*Four Class Model*		
class 2	estimate	t-stat	class 2	estimate	t-stat	class 2	estimate	t-stat	0.251	0.169	0.186	0.394
δ_0	0		δ_0	15.369	*5.38*	δ_0	-1.706	*-1.89*		*Posterior Probabilities*		
$\delta_{FOD/COW}$	0		$\delta_{FOD/COW}$	-0.176	*-1.82*	$\delta_{FOD/COW}$	0.126	*1.27*		(average for each class grouping)		
$\delta_{ORG/TOT}$	0		$\delta_{ORG/TOT}$	-0.027	*-0.01*	$\delta_{ORG/TOT}$	0.630	*0.48*		*Three Class Model*		
$\delta_{LAB/COW}$	0		$\delta_{LAB/COW}$	-51.947	*-3.94*	$\delta_{LAB/COW}$	1.572	*0.13*	0.987	0.974		0.978
$\delta_{MLK/TOT}$	0		$\delta_{MLK/TOT}$	-51.116	*-5.52*	$\delta_{MLK/TOT}$	-40.234	*-3.43*				

class 3	estimate	t-stat
δ_0	0	
$\delta_{FOD/COW}$	0	
$\delta_{ORG/TOT}$	0	
$\delta_{LAB/COW}$	0	
$\delta_{MLK/TOT}$	0	

class 3	estimate	t-stat
δ_0	-1.575	*-1.69*
$\delta_{FOD/COW}$	-0.063	*-0.69*
$\delta_{ORG/TOT}$	-1.514	*-0.66*
$\delta_{LAB/COW}$	18.008	*1.84*
$\delta_{MLK/TOT}$	-27.342	*-6.26*

class 4	estimate	t-stat
δ_0	0	
$\delta_{FOD/COW}$	0	
$\delta_{ORG/TOT}$	0	
$\delta_{LAB/COW}$	0	
$\delta_{MLK/TOT}$	0	

Table A2: 1st Order Elasticities for Different Classes - *Full Generalized Linear Model*

Class 1			*Class 2*			*Class 3*		
elasticity	estimate	t-stat	elasticity	estimate	t-stat	elasticity	estimate	t-stat
$\varepsilon_{M,NMQ}$	-0.184	*-10.19*	$\varepsilon_{M,NMQ}$	-0.080	*-4.68*	$\varepsilon_{M,NMQ}$	-0.058	*-5.33*
$\varepsilon_{M,LD}$	0.138	*6.32*	$\varepsilon_{M,LD}$	0.032	*1.46*	$\varepsilon_{M,LD}$	0.029	*2.47*
$\varepsilon_{M,LAB}$	0.109	*3.96*	$\varepsilon_{M,LAB}$	0.245	*8.85*	$\varepsilon_{M,LAB}$	0.089	*5.80*
$\varepsilon_{M,KAP}$	0.124	*5.40*	$\varepsilon_{M,KAP}$	0.196	*9.16*	$\varepsilon_{M,KAP}$	0.208	*15.64*
$\varepsilon_{M,COW}$	0.523	*18.57*	$\varepsilon_{M,COW}$	0.451	*16.79*	$\varepsilon_{M,COW}$	0.463	*25.81*
$\varepsilon_{M,FOD}$	0.203	*11.39*	$\varepsilon_{M,FOD}$	0.144	*8.16*	$\varepsilon_{M,FOD}$	0.201	*17.09*
$\varepsilon_{M,EN}$	0.023	*2.43*	$\varepsilon_{M,EN}$	0.055	*4.06*	$\varepsilon_{M,EN}$	0.012	*1.64*
$\varepsilon_{M,VET}$	0.087	*8.61*	$\varepsilon_{M,VET}$	0.041	*4.15*	$\varepsilon_{M,VET}$	0.057	*9.40*
$\varepsilon_{M,CHM}$	0.029	*3.23*	$\varepsilon_{M,CHM}$	0.001	*0.06*	$\varepsilon_{M,CHM}$	0.006	*1.16*
$\varepsilon_{M,T}$	0.029	*3.07*	$\varepsilon_{M,T}$	0.013	*1.90*	$\varepsilon_{M,T}$	0.016	*2.63*
$\varepsilon_{Y,X}$	1.043	*65.63*	$\varepsilon_{Y,X}$	1.079	*63.04*	$\varepsilon_{Y,X}$	1.008	*97.27*

(own second order elasticities are all negative, estimates upon request)

[i] This research commenced when the second author was a visiting scholar in the ARE Department at UC Davis, California, USA. Funding for this research was provided by the British Academy (SG-48134). The authors are grateful to Jakob Vesterlund Olsen, Landscentret, Skejby, Denmark for making the data available and to Prof. Julian Alston for initial discussions. Senior authorship is equally shared.

[ii] It also involves productive response to specific factors such as learning by doing and knowledge spillovers that may be technology-specific, which are beyond the scope of this study but will be addressed in subsequent work.

[iii] Tauer and Belbase (1987) deleted dairy farms from their data sample that participated in a particular (dairy diversion) program, that purchased most of their feed or replacement livestock, or that had a large proportion of non-milk sales.

[iv] Variables in levels such as the numbers of cows or hectares could also be included. However, as they are essentially "size" variables that are already included as production structure arguments, and thus are also taken into account in the LCM model, we only included the ratio measures. In preliminary investigation when we did try including such variables, however, their estimated coefficients tended to be quite significant.

[v] We initially used a organic subsidies/total subsidies variable but it had many missing values as there is only limited information for these categories of farms before 1990, and is also quite highly correlated with the chemicals ratios.

[vi] A measure of labor per total output rather than labor per cow was also tried in preliminary estimations.

[vii] The adaptation of this treatment for the transformation function was outlined by W. Erwin Diewert in private correspondence. Essentially, given the transformation function defined in equation (1), if all inputs are increased by a scale factor S, and one looks for another scalar factor (US) such that U times the initial vector of outputs **Y** is still on the transformation function, U(S) is implicitly defined by: $U(S)Y_1=F(U(S)Y_2,S\mathbf{X},T)$. The implicit function rule can then be used to calculate the derivative U'(S) evaluated at S=1: $U'(1) = (\Sigma_k dlnF(Y_2,\mathbf{X})/dlnX_k)/(1-dlnF(Y_2,\mathbf{X})/dlnY_2)$. If this measure exceeds one, it implies increasing returns to scale.

[viii] The "delta method" computes standard errors using a generalization of the Central Limit Theorem, derived using Taylor series approximations, which is useful when one is interested in some function of a random variable rather than the random variable itself (Gallant and Holly, 1980, Oehlert, 1992). For our application, this method uses the parameter estimates from our model and the corresponding variance covariance matrix to evaluate the elasticities at average values of the arguments of the function.

[ix] Such computations for a particular "Class" are based on using the highest posterior probability to assign farms to a particular group. If some farms have a reasonable probability of being in another class, it may be misleading to choose one reference technology. One way to deal with this is instead to compute a posterior-probability-weighted sum of the measures (Orea and Kumbhakar, 2004, Greene, 2002). However, if these probabilities are very high this is not likely to be a problem. As our average posterior probabilities range from 0.97 to 0.99 for the different classes, it does not make a substantive difference.

[x] Note that this might underestimate the efficiency of class 2 farms as they are more diversified and this only represents the milk production rather than total production.

[xi] If these fitted values are based on less aggregated data the results are roughly the same, although for class 3 the fitted values for either the class 1 or class 3 technology is virtually equivalent, potentially because the smaller farms' characteristics are not commensurate with taking advantage of the scale economies of the larger farms in class 1. This is true both when the fitted values are computed by observation and then averaged (this also results in a virtually identical fitted value for each own-class compared to the descriptive statistics) and when the results are fitted for the average values for each farm and then averaged.