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Detecting Technological Heterogeneity in New York Dairy Farms

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Abstract

Agricultural studies have often differentiated and estimated different technologies within a sample of farms. The common approach is to use observable farm characteristics to split the sample into several groups and subsequently estimate different functions for each group. Alternatively, unique technologies can be determined by econometric procedures such as latent class models. This paper compares the results of a latent class model with the use of *a priori* information to split the sample using dairy farm data in the application. Latent class separation appears to be a superior method of separating heterogeneous technologies.

***Keywords*:** parlor milking system, stanchion milking system, latent class model, stochastic frontier

Introduction

The issue of technological heterogeneity is of enormous relevance in studies of agricultural production since the agricultural sector is characterized by the presence of different technologies. For this reason, studies that use agricultural micro data often control for the possibility of technological heterogeneity. This has been traditionally done by selecting one main characteristic of the production process and dividing the sample based on this characteristic and subsequently estimating a different function for each group. Some of the characteristics that have been used in agricultural studies are: type *of seed* (Xiaosong and Scott); *variety* (Balcombe et al.); *land type* (Fuwa, Edmonds and Banik); or *full-time versus part-time farms* (Bagi).

Technological heterogeneity is also present in dairy farming where different production systems may be utilized. In empirical analysis this poses the problem of correctly identifying the groups of farms that operate under different technologies. As stated above, a common way to tackle this problem is to use observable farm characteristics to separate the sample into several groups and subsequently estimate a different function for each group. This approach has been used in previous dairy farm studies. For example, Hoch split a sample of Minnesota dairy farms into two groups based on location; Bravo-Ureta classified a sample of New England dairy farms based on the breed of the herd; Tauer (1998) estimated different cost curves for stanchion and parlor dairy farms; and Newman and Mathews estimated different output distance functions for specialist and non-specialist dairy farms.

However, the use of a single characteristic is probably an incomplete proxy for the characterization of a technology. The characteristics outlined above may not exhaust all technology differences that exist between farms. Feeding system usually varies across farms and may be an important descriptor of the technology. Additionally, there are unobserved (not measured) factors that may affect technologies. For example, one of these unobserved factors can be the genetic potential of the herds.

Alternatively, different technologies within a sample can be determined by statistical procedures. For example, groups of farms can be formed using cluster algorithms (Alvarez et al.). Econometric techniques, such as random coefficient models (Hildreth and Houck) and latent class models, (Lazarsfeld) can also be used to estimate different technologies within a sample. Random coefficient models assume that each observation is derived from a unique technology, and thus farm-specific coefficients are estimated. In contrast, latent class models, often referred to as mixture models, assume there are a finite number of groups underlying the data and estimate a different function for each of these groups. Since we believe that a discrete number of farm groups better describes the dairy sector we will elect to utilize latent class models.

The purpose of this paper is to compare the results of latent class models with the use of *a priori* information to split the sample. For a sample of New York dairy farms we use two milking systems, namely, stanchion and parlor, as the observed characteristic that will allow us to split the data. Stanchion farms use conventional stall housing for dairy cows, where cows are milked and often housed in individual stalls with the farmer moving from stall to stall in a stooped position to milk the cows, while in parlor farms cows enter a raised platform for milking and leave once they are milked. These are distinct milking systems, and it would be expected that production characteristics would differ between these two systems as measured by output elasticities, returns to scale, input substitutability and efficiency.[1]

Our basic model is a production function that we implement in the framework of a stochastic frontier model (Aigner, Lovell and Schmidt). Stochastic frontiers are widely used to estimate production functions where individual observations are constrained to be below the stochastic frontier (with sampling error). Several authors have estimated latent class models in a stochastic frontier framework (*e.g.*, Orea and Kumbhakar; Greene, 2005). Comparison between the stochastic frontiers of the two milking systems and a stochastic frontier latent class model allows us to determine whether the milking system is a relevant factor in determining technology class.

The remainder of this paper is organized as follows. The following section presents the data used. Next, the methodology is explained. This is followed by the empirical model and results. Finally, the paper ends with concluding remarks.

Data

The data used in this study were taken from the annual New York State Dairy Farms Business Summary (NYDFBS), which are farm level data collected on a voluntary basis from 1993 through 2004 (Knoblauch, Putnam and Karszes). The sample of 817 unique farms does not necessarily represent the population of New York dairy farms[2]. The number of farms participating varies each year, producing an unbalanced panel data set of 3,304 observations.

In order to estimate the production function we specify one output and six inputs. We specify only one output since these farms are highly specialized in milk production;

milk must constitute at least 85 percent of the revenue for a farm to be included in the data set, and much of the remaining revenue are cull cow sales, a necessary by-product of dairy production (Knoblauch, Putnam and Karszes). None-the-less miscellaneous items are sold from these farms and these items require inputs to produce. Therefore, we add all non-milk output items to our single output by converting each item into equivalent pounds of milk by dividing revenue by the price of milk. The inputs are COWS (average number of cows), FEED (accrual purchased feed measured in US $[3]), CAPITAL (service flow from land and buildings estimated as five percent of market value plus accrual machinery hire expenses, accrual machinery repair expenses and machinery depreciation), LABOR (total worker equivalents used on the farm), CROP (fertilizer, seeds, spray and fuel accrual expenses) and OTHER (veterinary and medications, breeding, electricity and milk marketing accrual expenses). Table 1 displays the descriptive statistics of these variables, the single input productivity measures of milk production per cow, milk per acre and cows per acre of cropland as well as a dummy variable named DPARLOR that takes the value of one if the farm uses a parlor milking system and 0 if the farm uses a stanchion system.

Table 1. Summary statistics on New York Dairy Farm Business Summary data (1993-2004)

	Mean	Standard Deviation	Minimum	Maximum
Milk (lbs.)	4,270,430	5,650,650	173,868	44,407,600
OUTPUT (lbs. equiv.)	4,911,670	6,484,540	194,779	53,100,000
COWS (number)	203	242	19	2,172
FEED (U.S. $)	157,487	228,524	3,061	2,483,210
CAPITAL (U.S. $)	94,353	113,827	5,197	969,906
LABOR (annual workers)	5.25	4.82	0.73	36.14
CROP (U.S. $)	40,375	53,135	365.672	596,442
OTHER (U.S. $)	62,239	83,451	2,011	672,933
Milk per cow (lbs.)	19,203	3,560	5,796	28,895
Milk per acre (lbs.)	7,179	8,849	700.608	269,578
Cows per acre	0.36	0.41	0.07	13.17
DPARLOR	0.57	0.50	0.00	1.00
Number of observations		3,304		

Methodology

We use the stochastic frontier approach which came into prominence in the late 1970s as a result of the work of Aigner, Lovell and Schmidt.[4] A stochastic frontier production function may be written as:

$$y = f(x) \cdot \exp(\varepsilon); \ \varepsilon = v - u \tag{1}$$

where y represents the output of each farm, x is a vector of inputs, $f(x)$ represents the technology, and ε is a composed error term. The component v captures statistical noise and is assumed to follow a normal distribution centered at zero, while u is a non-negative term that reflects the distance between the observation and the frontier (i.e., technical inefficiency) and is assumed to follow a one-sided distribution (half-normal in our case). These models are usually estimated using maximum likelihood techniques.

We estimate two different stochastic frontier models. First we estimate a model for both the parlor and stanchion farms that uses the Battese and Coelli (1992) specification of the inefficiency term:

$$\ln y_{it} = f(x_{it}) + \varepsilon_{it}; \qquad \varepsilon_{it} = v_{it} - u_{it} \qquad u_{it} = \exp\left(-\eta(\tau - T)\right)\cdot u_i \tag{2}$$

where subscript i denotes farm, t indicates time, τ is the actual period, T is the total number of periods in the sample and η is a parameter to be estimated. If η is positive (negative) implies that efficiency increases (decreases) over time.

Our second model is a stochastic frontier latent class model (Greene, 2005), which is specified as:

$$\ln y_{it} = f(x_{it})\big|_j + \varepsilon_{it}\big|_j; \qquad \varepsilon_{it}\big|_j = v_{it}\big|_j - u_{it}\big|_j; \qquad u_{it}\big|_j = \exp\left(-\eta\big|_j(\tau - T)\right)\cdot u_i\big|_j \tag{3}$$

where j represents the different classes (groups). The vertical bar means that there is a different model for each class j. It is important to note that the model assumes that each farm belongs to the same group over the sample period. The likelihood function (LF) for each farm i at time t for group j is (Greene, 2005):

$$LF_{ijt} = f\left(y_{it}\middle|x_{it,}\beta_j, \sigma_j, \lambda_j\right) = \frac{\Phi\left(\lambda_j \cdot \varepsilon_{it|j} / \sigma_j\right)}{\Phi(0)} \cdot \frac{1}{\sigma_j} \cdot \phi\left(\frac{\varepsilon_{it|j}}{\sigma_j}\right) \tag{4}$$

where $\varepsilon_{it|j} = \ln y_{it} - \beta_j' x_{it}$, $\sigma_j = \left[\sigma_{uj}^2 + \sigma_{vj}^2\right]^{1/2}$, $\lambda_j = \sigma_{uj} / \sigma_{vj}$, and ϕ and Φ denote the standard normal density and cumulative distribution function respectively.

The likelihood function for farm i in group j is obtained as the product of the likelihood functions in each period.

$$LF_{ij} = \prod_{t=1}^{T} LF_{ijt} \quad (5)$$

The likelihood function for each farm is obtained as a weighted average of its likelihood function for each group *j*, using as weights the prior probabilities of class *j* membership. The prior probabilities of class membership can be sharpened using separating variables but as Orea and Kumbhakar stated, a latent class model classifies the sample into several groups even when sample-separating information is not available. In this case, the latent class structure uses the goodness of fit of each estimated frontier as additional information to identify groups.

$$LF_{i} = \sum_{j=1}^{J} P_{ij} LF_{ij} \quad (6)$$

The overall log-likelihood function is obtained as the sum of the individual log-likelihood functions:

$$\log LF = \sum_{i=1}^{N} \log LF_{i} = \sum_{i=1}^{N} \log \sum_{j=1}^{J} P_{ij} \prod_{t=1}^{T} LF_{ijt} \quad (7)$$

The log-likelihood function can be maximized with respect to the parameter set $\theta_j=(\beta_j, \sigma_j, \lambda_j, \delta_j, \eta_j)$ using conventional optimization methods (Greene, 2005). Furthermore, the estimated parameters can be used to estimate the posterior probabilities of class membership using Bayes Theorem:

$$P(j/i) = \frac{P_{ij} LF_{ij}}{\sum_{j=1}^{J} P_{ij} LF_{ij}} \quad (8)$$

Empirical model and results

The empirical specification of the production function is translog. The dependent variable is milk production plus other revenue converted into equivalent pounds of milk. Six inputs are defined in the Data section and include: COWS (cows), FEED (purchased feed), CAPITAL (capital flow), LABOR (total workers), CROP (crop expenses) and OTHER (veterinary and medications, breeding, electricity and milk marketing expenses). The input variables were divided by their geometric means so that the estimated first order coefficients from the translog can be interpreted as the production elasticities evaluated at the sample geometric means. Additionally, a time trend plus a squared time trend are introduced to account for technological and other changes. In order to control for different regional conditions we use a set of dummy variables (DSOUTH, DNORTHWEST, DEAST and DNORTHEAST)[5]. The omitted category is the Northeast. Finally, we control for Bovine Somatotropin (bST) usage by means of three dummy variables. BST1 takes the value of one if 25 percent or fewer of the cows were treated with bST sometime during their lactation; BST2 takes the value of one if between 25 to 75 percent of the cows were treated with bST; and BST3 takes the value of one if over 75 percent of the cows in the herd were treated. The reference then is for farms not using bST during the year.

The production functions to be estimated for parlor and stanchion farms are:

$$\ln y_{it} = \beta_0 + \sum_{l=1}^{L} \beta_l \ln x_{lit} + \frac{1}{2}\sum_{l=1}^{L}\sum_{k=1}^{L} \beta_{lk} \ln x_{lit} \ln x_{kit} + \lambda_t \cdot t + \lambda_{tt} \cdot t^2 + \sum_{z=1}^{z=3} \gamma_z \cdot DLOC_{zi} + \sum_{h=1}^{h=3} \alpha_h \cdot DBST_{hit} + v_{it} - u_{it}; \quad u_{it} = \exp\left(-\eta \cdot (\tau - T)\right) \cdot u_i \qquad (9)$$

where t is a time trend, and *DLOC* are the regional dummies.

The equation of the latent class model is then represented as:

$$\ln y_{it} = \beta_0\big|_j + \sum_{l=1}^{L}\beta_l\big|_j \ln x_{lit} + \frac{1}{2}\sum_{l=1}^{L}\sum_{k=1}^{L}\beta_{lk}\big|_j \ln x_{lit}\ln x_{kit} + \lambda_t\big|_j \cdot t + \lambda_{tt}\big|_j \cdot t^2 + \sum_{z=1}^{z=3}\gamma_z\big|_j DLOC_{zi} + \sum_{h=1}^{h=3}\alpha_h\big|_j DBST_{hit} + v_{it}\big|_j - u_{it}\big|_j;\;\; u_{it}\big|_j = \exp\left(-\eta\big|_j(\tau - T)\right)\cdot u_i\big|_j \quad (10)$$

In the latent class model the researcher specifies the number of groups *a priori* since the number of groups is not a parameter to be estimated. To choose the number of groups, Information Criteria such as AIC and SBIC are typically used[6] (e.g., Orea and Kumbhakar). Using these criteria, the model with two groups is the preferred one for these data.

Table 2 reports the estimation results of equations 9 and 10.[7] All the first order coefficients are positive and significant in all models. As expected, the Bovine Somatotropin dummies indicate that a higher use of this growth hormone increases production *ceteris paribus*. Moreover, farms located in the East are the least productive farms, with the farms in the Northeast the most productive. The Northeast, often referred to as the North Country, is primarily a dairy region with few other commodities produced. Dairy farms have a comparative advantage in this region. The soils are generally poorer quality than in the valley regions of the other regions, and the growing season is shorter. Yet, farmers in the Northeast are able to obtain good feed rations using produced forage augmented with grain purchases. The South and East regions consist of hill and valley farms, with many of the hill farms disappearing, since those are situated on poorer soils. In contrast the Northwest generally has the most consistent good quality soils and is the region where many of the larger farms have developed. The Northwest is the second most productive region after the Northeast.

Table 2. Stochastic frontier translog production function estímates

	Milking system		Latent class model	
	Parlor	**Stanchion**	**Group 1**	**Group 2**
CONSTANT	15.506***	14.191***	14.895***	14.954***
COWS	0.643***	0.621***	0.763***	0.398***
FEED	0.126***	0.126***	0.065***	0.209***
CAPITAL	0.050***	0.057***	0.026***	0.074***
LABOR	0.087***	0.054***	0.071***	0.085***
CROP	0.021***	0.036***	0.028***	0.040***
OTHER	0.145***	0.196***	0.103***	0.306***
0.5· COWS· COWS	-0.353***	-0.134	-0.291***	0.065
0.5· FEED· FEED	0.034*	0.067**	-0.055*	0.183***
0.5· CAPITAL· CAPITAL	-0.031	0.001	-0.062***	0.057
0.5· LABOR· LABOR	-0.205***	-0.020	-0.093**	0.024
0.5· CROP· CROP	-0.015	0.029	0.008	0.017
0.5· OTHER· OTHER	0.039	0.097***	-0.017	0.298***
COWS· FEED	0.097***	-0.008	0.090**	-0.026
COWS· CAPITAL	0.056*	0.105**	0.091***	0.032
COWS· LABOR	0.230***	-0.021	0.085**	0.095
COWS· CROP	-0.006	0.005	0.095***	-0.037
COWS· OTHER	0.001	0.008	-0.060**	-0.118*
FEED· CAPITAL	-0.045**	-0.043**	-0.022	-0.040*
FEED· LABOR	-0.082***	0.040	-0.004	-0.003
FEED· CROP	0.005	-0.035*	-0.059***	-0.013
FEED· OTHER	-0.023	-0.042	0.074***	-0.126***
CAPITAL· LABOR	-0.015	-0.056**	-0.029	-0.035
CAPITAL· CROP	0.011	-0.039**	0.003	-0.031
CAPITAL· OTHER	0.006	-0.011	0.009	-0.017
LABOR· CROP	0.047**	0.043*	-0.010	0.085***
LABOR· OTHER	-0.009	-0.050	0.010	-0.101**
CROP· OTHER	-0.025	-0.007	-0.033**	0.008
TIME TREND	-0.001	-0.005*	0.007***	-0.020***
SQUARED TIME TREND	-0.001***	0.000**	-0.001***	0.000
DSOUTH	-0.085***	-0.016	-0.028***	-0.084***
DNORTHWEST	-0.075***	0.024	-0.026***	0.009
DEAST	-0.091***	-0.042***	-0.057***	-0.064***
DBST1: Less than 25%	0.015**	0.033***	0.024***	0.009
DBST2: 25-75%	0.061***	0.044***	0.051***	0.063***
DBST3: Higher than 75%	0.088***	0.060***	0.068***	0.125***
η	-0.019***	-0.026***	-0.019***	-0.005
$\sigma = [\sigma_v^2 + \sigma_u^2]^{1/2}$	0.169***	0.239***	0.910***	0.843***
$\lambda = \sigma_u / \sigma_v$	2.802***	3.746***	0.028	0.034
Observations	1,886	1,418	3,304	
Log. LF	2,189	1,409	3,724	

Note: *,**,*** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 3 shows the averages of some representative variables for the two groups obtained in the latent class model as well as for both milking systems. There are large differences between parlor and stanchion farms and between the two groups identified in the latent class model, labeled ‘group 1’ and ‘group 2’. In particular, parlor farms and group 1 farms are larger in size and have higher input average productivities than stanchion farms and group 2 farms respectively. On the other hand, group 1 of the latent class model is formed mainly by parlor farms, while in group 2 there are relatively more stanchion farms than parlor farms. Yet, there are significant differences among those groups (i.e., parlor vs. group 1 and stanchion vs. group 2) especially in size. Therefore, although parlor and stanchion milking appear to differentiate our sample into unique technologies, other characteristics than simply the milking system appears important to differentiate the sample farms. A closer investigation of the estimated results of the production functions may provide insights.

Table 3. Characteristics of dairy farm production systems (sample averages)

	Milking system		Latent class model	
	Parlor	Stanchion	Group 1	Group 2
Number of observations	1,886	1,418	2,307	997
DPARLOR	1	0	0.60	0.50
Milk (lbs.)	6,492,910	1,314,450	5,140,050	2,258,190
Cows	301	73	238	123
Labor (annual workers)	7.21	2.64	5.96	3.62
Land (acres)	729	307	598	434
Yield per cow (lbs.)	20,308	17,734	20,181	16,940
Milk per acre (lbs.)	8,713	5,137	8,107	5,031
Milk per worker (lbs.)	808,569	505,947	728,057	564,460
Purchased feed ($) per cow	739	613	710	627
Cows per acre	0.42	0.28	0.39	0.29
Technical efficiency	0.89	0.85	0.89	0.88

Output elasticities from parlor and stanchion farms are very similar. The null hypothesis that both milking systems are characterized by the same output elasticities at the sample means was tested using a t-test for each input and it was rejected only for OTHER at the 99% confidence level and for LABOR at the 95% confidence level. LABOR is much more productive on the parlor milking farms as shown later in Figure 2.

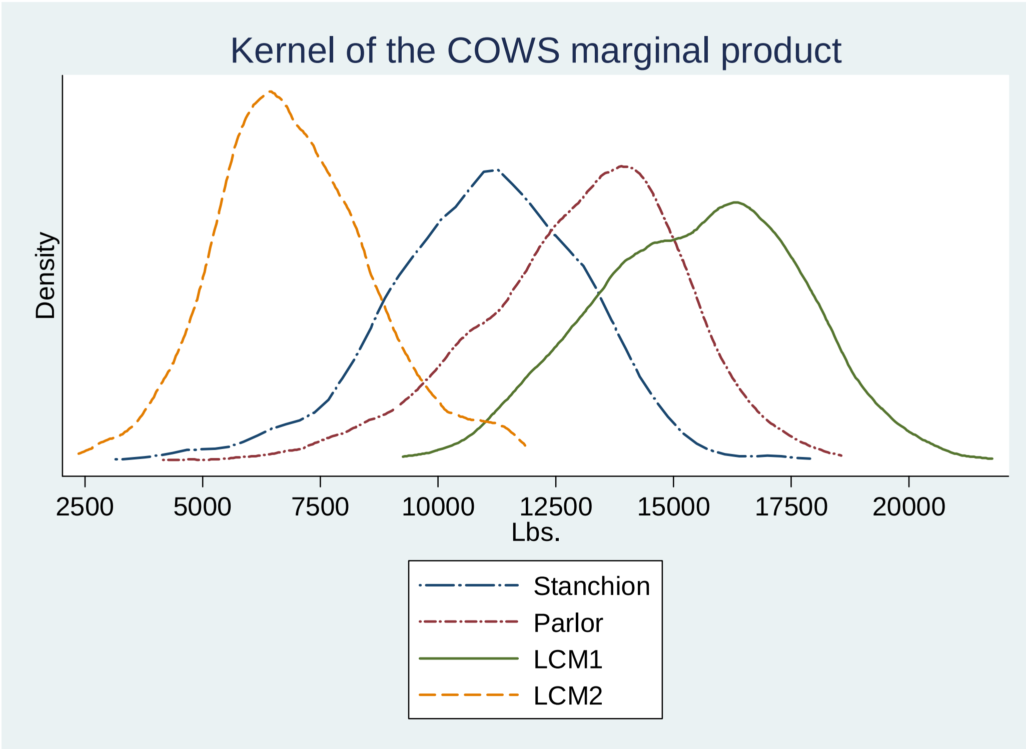
On the other hand, the estimation of the latent class model found two technologies that seem very different from each other. In this case the tests of equal output elasticities between groups indicate that the output elasticities are different for COWS, FEED, CAPITAL and OTHER, but not LABOR. It appears that the latent models are differentiating based upon minute technology differences which may include cow genetics, feeding system, amount of capital utilized (including parlors), and miscellaneous inputs.

Marginal products of the inputs can be calculated as:

$$MP_{itl} = \frac{\varepsilon_l \cdot y_{it}}{x_{it}} \tag{11}$$

where ε_l is the weighted averaged of the output elasticity using as weights the posterior probabilities in the latent class model and the output elasticity in the geometric means in the milking system estimates. Figure 1 shows the kernel distributions of the marginal products for all groups. These distributions show that for most inputs the distribution of the marginal products of the stanchion and parlor farms are rather similar except for labor, but that the distribution of the marginal products of the latent class models groups are clearly differentiated for all inputs except labor. Especially telling is the marginal product of the cow input, which is measured simply as the number of cows. Cows are slightly more productive in parlor farms than in stanchion farms, but the differential is most striking between the latent groups, with the MP of latent group 2 being much lower. Apparently, farms with low producing cows, due to inferior genetics, disease, poor feeding and other poor management practices are being differentiated from farms with higher productive cows. Milk per cow has always been a bellwether indicator of good management. Size may simply be associated with management.

In contrast, the MP of purchased feed which is measured in dollars of expenditures is much higher in latent group 2 compared to latent group 1, possibly reflecting the fact that the farms in latent group 2 are not using enough feed, since they use on average only $627 per cow compared to $710 for latent group 1. With capital, although the distribution of MPs of parlor and stanchion are essentially identical, the MP of latent group 1 is much lower than latent group 2. Yet, as indicated earlier, the MP of labor is almost identical between the two latent groups, which is not the case for parlors and stanchions, with the MP of labor in stanchion farms being much lower. With the crop input, it appears that stanchion farms are similar to latent group 2, while parlor farms are similar to latent group 1.


Kernel of the COWS marginal product
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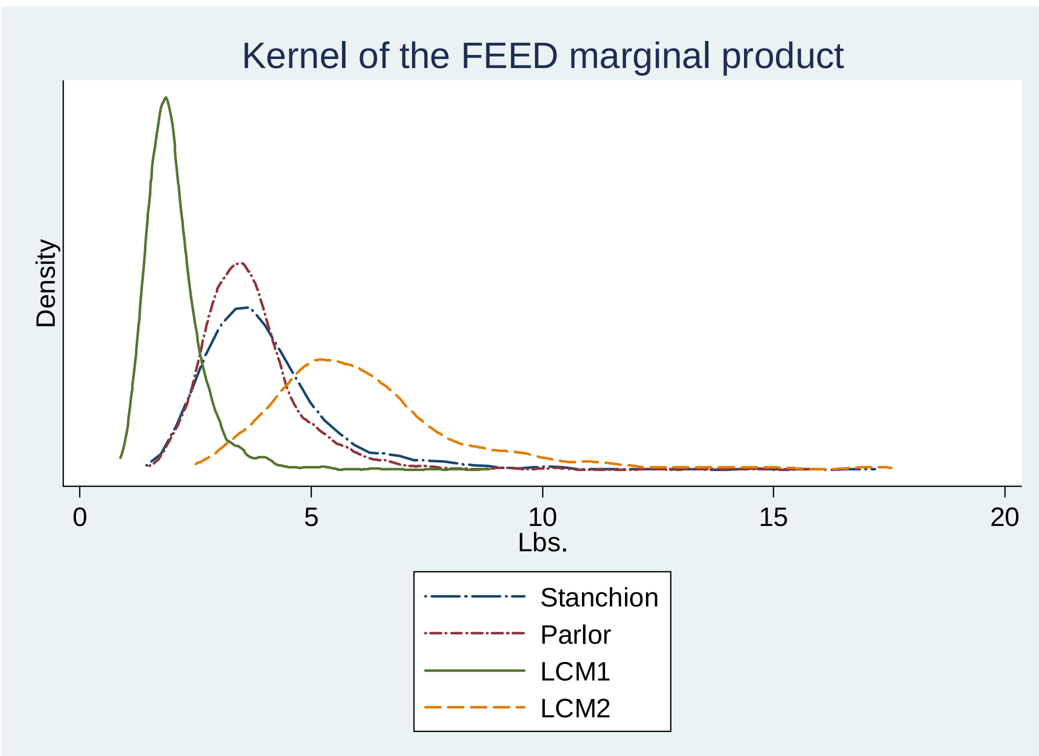
LCM2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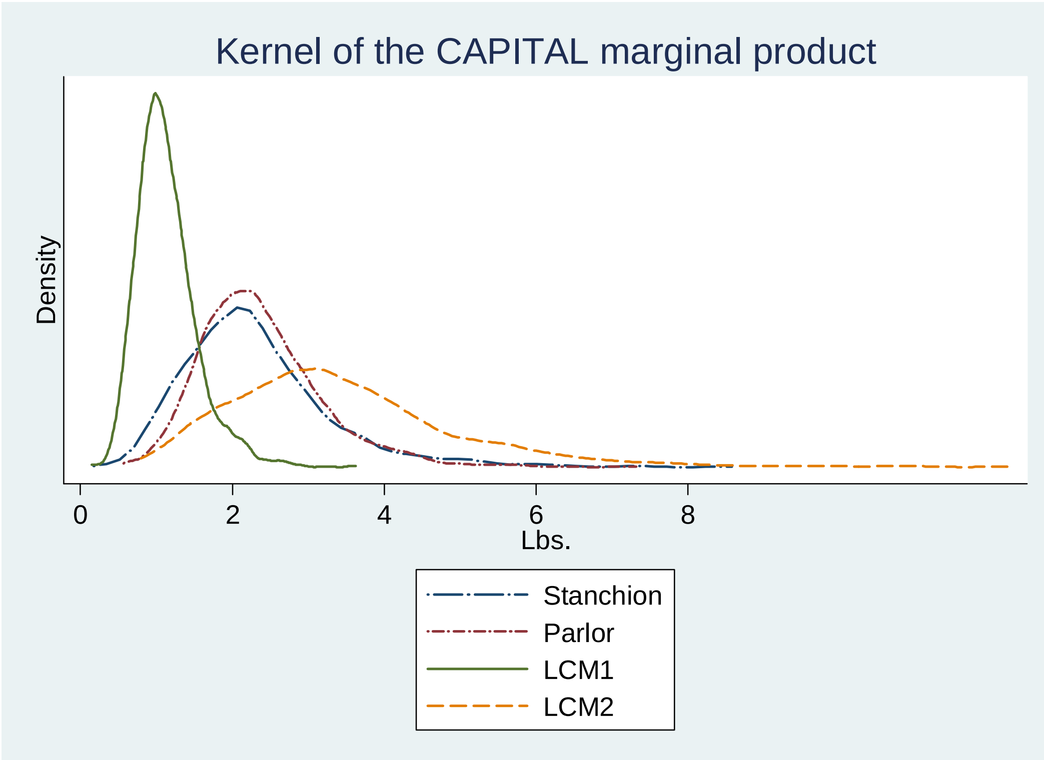
Parlor
LCM1
LCM2


Kernel of the CAPITAL marginal product
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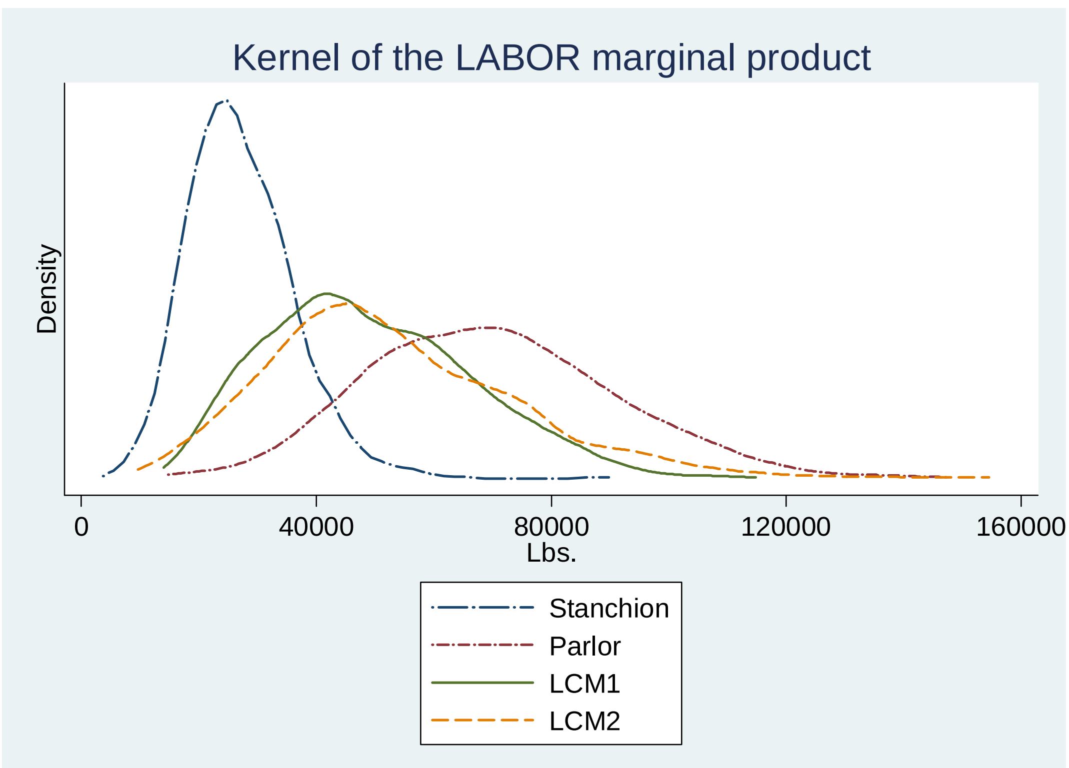
Stanchion
Parlor
LCM1
LCM2


Kernel of the LABOR marginal product
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120000
160000
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Stanchion
Parlor
LCM1
LCM2

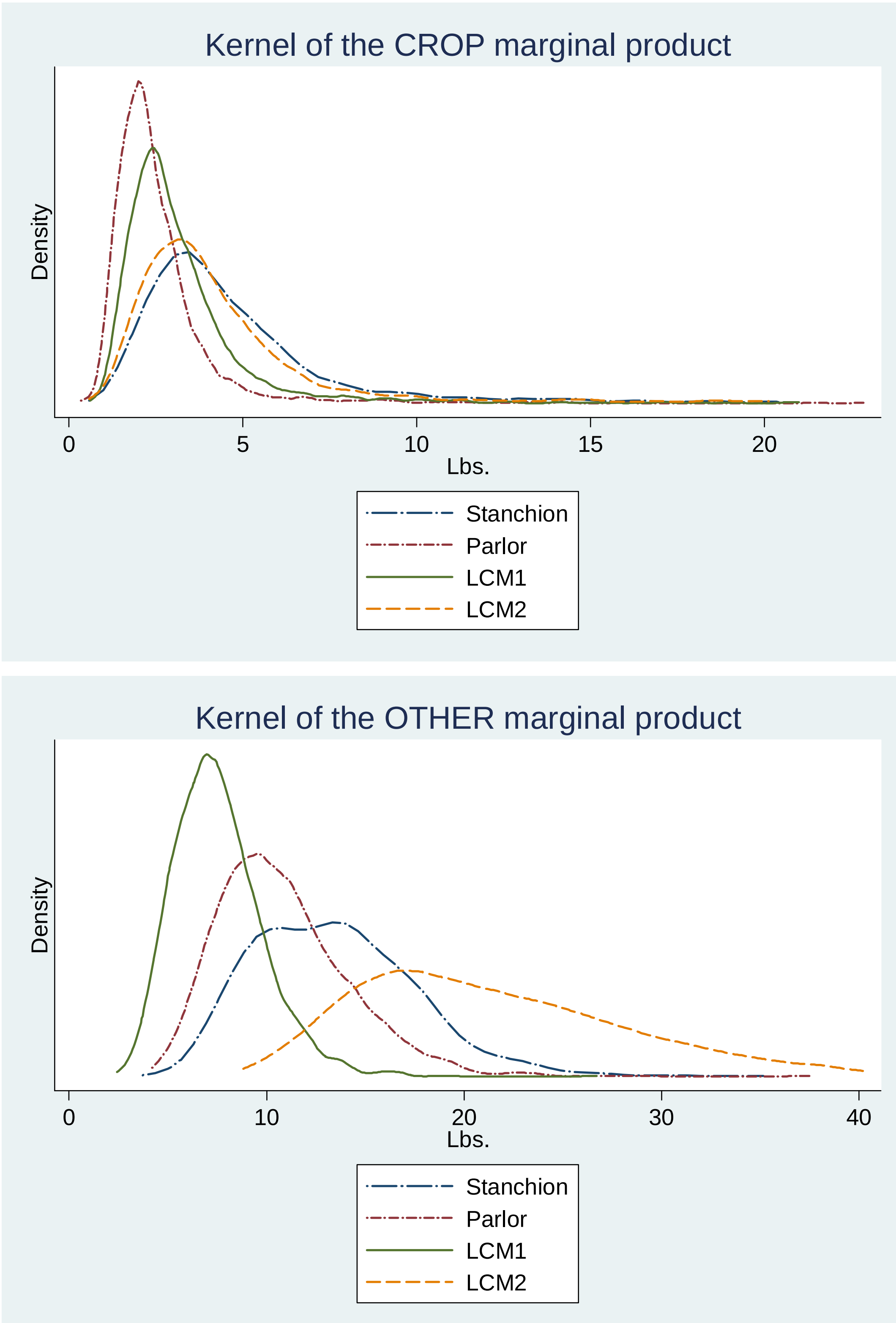

Figure 1. Kernel distributions of the marginal products for all groups

Differences in Technical Efficiency

Technical efficiency (*TE*) reflects the ability of a farm to produce the maximum level of output from a given set of inputs. A technical efficiency index can be calculated using the following expression (the dependent variable must be in natural logs):

$$TE = \exp(-\hat{u}) \qquad (12)$$

where the inefficiency term, u, is separated from the other error component using the formula developed by Jondrow *et al*.

Stanchion farms are less efficient on average than parlor farms. Although these stanchion barns are functionally operational, many are obsolete. Stanchion milking is labor intensive, and physically demanding. These milking systems also generally lack the monitoring equipment found in most parlors. The parameter η is negative and statistically significant for stanchion farms and group1 from the latent class model, implying that technical efficiency decreases over time for these two groups.[8] Figure 2 shows the evolution of these average technical efficiency levels. Efficiency declines over time for parlors as well, but the decline is greater for the stanchion farms. These stanchion farms continue to depreciate in efficiency as parlor milking systems dominate the industry. Similarly, farms which belong to group 1 are more efficient than farms belonging to group 2 in the latent class model. However, due to the decreasing pattern in group 1 and the increasing pattern of group 2, technical efficiency is higher for the group 2 than group 1 in the last years of the sample.

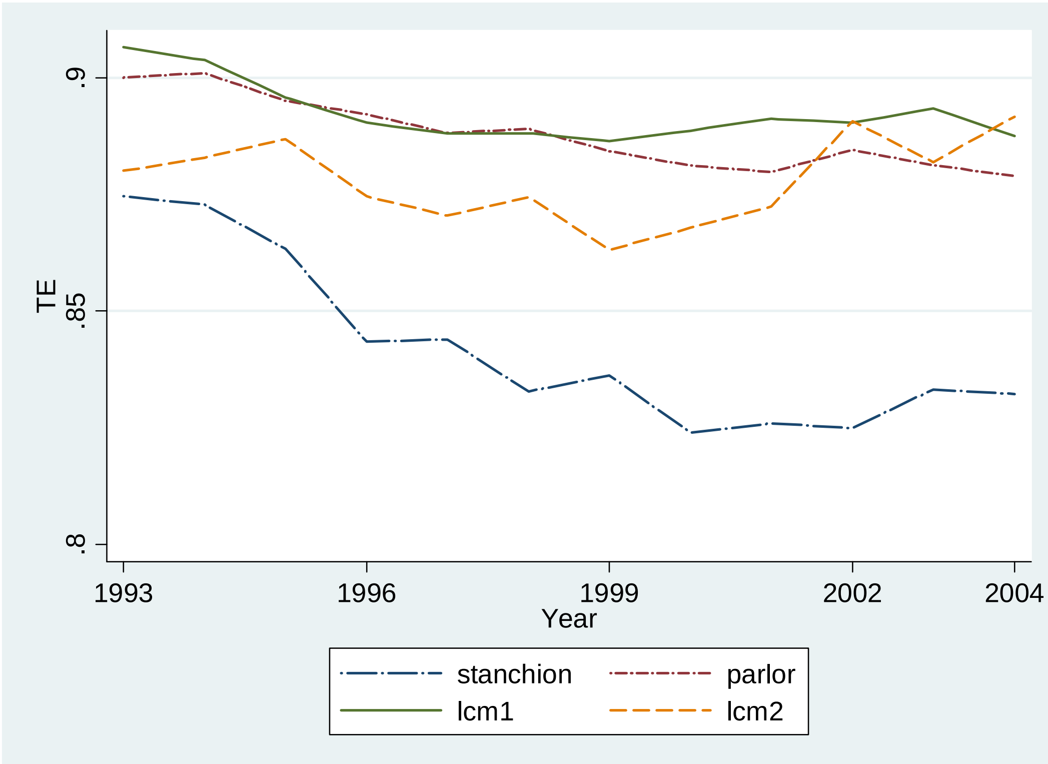

Figure 2. Average technical efficiency over time

Conclusions

In this paper we investigate the identification of farm grouping within a sample where farms may not share the same technology. To accomplish this task, we compare the typical approach in the literature, i.e., splitting the sample based on an observable characteristic, with a latent class model, which is a relatively modern econometric procedure that uses statistical properties for differentiation.

The empirical exercise uses data from a sample of New York dairy farms. Because dairy farms are often separated into stanchion and parlor milking systems, we estimate separated stochastic production frontiers for stanchion milking farms and for parlor milking farms. We also estimate a stochastic frontier latent class model that identifies two groups of dairy farms based on their unobserved (latent) technological differences. Comparison of the results from the two approaches implies that milking system is only a partial determining factor of technology differences.

The latent class model was able to classify the farms into two groups that showed much higher technological differences than those obtained by splitting the sample using milking system as the separation criterion. Therefore, from a methodological point of view if researchers suspect that farms in the sample do not share the same technological characteristics, we suggest that they use latent class models to control for heterogeneity.

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[1] Controlling for differences in milking system is rather common in studies of dairy production. See, for example, El-Osta and Morehart, Kompas and Che and Tauer (1993, 1998).

[2] Using dairy farm sample based on voluntary participation is usual in the literature. For instance, Ahmad and Bravo-Ureta, and Newman and Matthews, to name just a few.

[3] All the monetary variables are expressed in 2004 US$. The US CPI index was used to deflate the variables.

[4] See Kumbhakar and Lovell or Greene (2008) for good overviews.

[5] The composition of these variables is shown in the appendix.

[6] The statistics can be written as: $AIC = -2 \cdot \log LF(J) + 2 \cdot m$; $SBIC = -2 \cdot \log LF(J) + \log(n) \cdot m$, where *LF(J)* is the value that the likelihood function takes for *J* groups, *m* is the number of parameters used in the model and *n* is the number of observations. The preferred model will be that for which the value of the statistic is lowest.

[7] All models were estimated using Limdep 9.0

[8] However, it increases for some periods. The model implies that TE is a monotonic function of time, so this aberration occurs because the panel is unbalanced and the computations are based upon individual observations.

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Appendix

Counties of New York in each region

DSOUTH: Allegany, Cattaraugus, Chautauqua, Chemung, Columbia, Cortland, Delaware, Schuyler, Steuben, Sullivan, Tioga, Tompkins.

DNORTHWEST: Cayuga, Erie, Genesee, Livingston, Niagara, Ontario, Orleans, Seneca, Wayne, Wyoming, Yates.

DEAST: Albany, Chenango, Herkimer, Madison, Montgomery, Oneida, Onondaga, Otsego, Rensselaer, Saratoga, Schenectady, Schoharie, Washington.

DNORTHEAST: Clinton, Franklin, Jefferson, Lewis, Saint Lawrence.