Modeling Unobserved Heterogeneity in New York Dairy Farms: One-Stage versus Two-Stage Models

Antonio Alvarez, Julio del Corral, and Loren W. Tauer

Agricultural production estimates 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 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. Latent class separation appears to be a superior method of separating heterogeneous technologies and suggests that technology differences are multifaceted.

Key Words: parlor milking system, stanchion milking system, latent class model, stochastic frontier

The estimation of production (and cost or profit) functions usually relies on the assumption that the underlying technology is the same for all producers. However, it is possible that technological heterogeneity exists among farms, which means that some farms in an industry use different technologies. In such a case, estimating a common technology to all farms is not appropriate because it can yield biased estimates of the technological characteristics.

The issue of technological heterogeneity is of enormous relevance in studies of agricultural production when an agricultural sector is believed to be characterized by different technologies. Management advice or policy implications may differ for these different sub-groups. For this reason, studies often control for the possibility of technological heterogeneity, traditionally accomplished by selecting a major characteristic of the production process, dividing the sample based on this characteristic, and subsequently estimating different functions for each group. Some characteristics that have been used in agricultural studies are type of seed or variety planted (Xu and Jeffrey 1998, Balcombe et al. 2007), land type (Fuwa, Edmonds, and Banik 2007), location (Battese, Malik, and Broca 1993), or full-time versus part-time farms (Bagi 1984).

Technological heterogeneity is also believed to be present in dairy farming where different production systems may be utilized. Thus, in dairy empirical analysis it is essential to correctly identify the groups of farms that operate under different technologies. Separating a sample of dairy farms into several groups and subsequently estimating separate functions was done by Hoch (1962), who split a sample of Minnesota dairy farms into two groups based on location; Bravo-Ureta (1986), who classified a sample of New England dairy farms based on the breed of the herd; Tauer (1998), who estimated different cost curves for stanchion and parlor dairy farms; Newman and Matthews (2006), who estimated different output distance functions for specialist and non-specialist dairy farms; Brümmer, Glauben, and Thijssen (2002), who estimated separate stochastic dairy production distance functions for three European Countries; and Moreira and Bravo-Ureta

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(2010), who estimated different production functions for three Southern Cone countries to subsequently estimate meta-technology ratios.

However, the use of a single or even multiple characteristics probably serves as an incomplete proxy to characterize a technology, since these characteristics may not exhaust all technology differences that exist between farms. Milking or feeding systems usually vary across dairy farms and may be an important descriptor of the technology, but there are additional unobserved (not measured) factors that may reflect technology differences. For example, one of these unobserved factors could be the genetic potential of the dairy herd.

Rather than use prior separators, different technologies within a sample can be isolated using statistical procedures. Groups of farms can be delineated using either cluster algorithms (Alvarez et al. 2008) or econometric techniques, such as the approach used in Kumbhakar, Tsionas, and Sipiläinen (2009), where a system approach was used to estimate the production technologies and the choice equation simultaneously, random coefficient models (Emvalomatis 2012), or latent class models (Alvarez and del Corral 2010, Sauer and Morrison Paul 2013). 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 that there are a finite number of groups underlying the data and estimate a different function for each of these groups. For the purpose of this paper, the use of a latent class model seems more appropriate than a random coefficient model given that the results from a latent class model can be easily compared, especially if the number of groups is the same, with the results obtained from separating a sample of dairy farms into several groups and subsequently estimating separate functions.

Although a production relationship can be modeled by various functions such as cost, profit, or revenue, our model is a production function that we implement in the framework of a stochastic frontier model (Aigner, Lovell, and Schmidt 1977). 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 2004, Greene 2005). We use two milking systems —namely, stanchion and parlor—which are often used to differentiate dairy farms, as the observed characteristic to split the data and compare those results with our latent model results. 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 milking system would be a relevant factor in determining technology class if the grouping in the latent class model is also made using this criterion without utilizing this information in the latent class model estimation.

The contribution to the literature of this paper is twofold. First, we provide evidence that using a latent class model can be more appropriate than estimating functions with different technologies, using a two-stage procedure where in the first step farms are grouped using some variable and subsequently separated functions are estimated. To the best of our knowledge there is no paper that has explicitly made such a comparison. Secondly, this paper estimates technology differences for dairy farms where substantial structural changes are occurring with significant policy implications.

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

Data

The data used, which were taken from the annual New York State Dairy Farms Business Summary (NYDFBS), are farm-level data collected on a voluntary basis from 1993 through 2004 (Knoblauch, Putnam, and Karszes 2005). As a voluntary participant data sample, the sample of 817 unique farms does not necessarily represent the population of New York dairy farms.[1] The number of farms participating varies each year, producing an unbalanced panel data set of 3,304 observations. Those data are differentiated into stanchion (1,418 ob-

[1] Using a dairy farm sample based on voluntary participation is usual in the literature. Examples include Ahmad and Bravo-Ureta (1995), Newman and Matthews (2006), and Byma and Tauer (2010).

servations) and parlor (1,886 observations) milking systems. There was attrition in NYDFBS participation over this period, so the number of observations per year decreases over time, especially for stanchion farms. Fifty-one out of 762 farms switched from stanchion to parlor milking over this time period, but not vice versa, and those farms were coded and included as stanchion or parlor depending on the milking system that was used each year. Individual farm effects were not modeled.

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 might differ between these two systems as measured by output elasticities, returns to scale, input substitutability, and efficiency.[2]

In order to estimate the production function, we specify one output and six inputs. One output only is specified since these farms are highly specialized in milk production; milk sales must constitute at least 85 percent of the revenue for a farm to be included in the original data set, and much of the remaining revenue are cull cow sales, a necessary by-product of dairy production (Knoblauch, Putnam, and Karszes 2005). Nonetheless, 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 of these items by the price of milk. Six inputs are defined and include COWS (average number of cows during the year), FEED (accrual purchased feed measured in U.S. dollars[3]), CAPITAL (service flow from land and buildings estimated as 5 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, which takes the value of one if the farm uses a parlor milking system and 0 if the farm uses a stanchion system.

Methodology

A stochastic frontier production function is written as

$$(1) \qquad y = f(x) \cdot \exp(\varepsilon)\,,\ \varepsilon = v - u\,,$$

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 (Aigner, Lovell, and Schmidt 1977).[4] The component v captures statistical noise and is assumed to follow a normal distribution centered at zero, while u is a nonnegative 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).

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

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

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), that implies that efficiency increases (decreases) over time.

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

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

[2] Controlling for differences in milking systems is rather common in studies of dairy production. See, for example, El-Osta and Morehart (2000), Kompas and Che (2006), and Tauer (1993, 1998).

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

[4] See Kumbhakar and Lovell (2000), Greene (2008), or Amsler, Lee, and Schmidt (2009) for good overviews.

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	--	0.00	1.00
Number of observations: 3,304				

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

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

where $\varepsilon_{it|j} = \ln y_{it} - \beta_j' x_{it}$, $\sigma_j = [\sigma_{uj}^2 + \sigma_{vj}^2]^{½}$, $\lambda_j = \sigma_{uj}/\sigma_{vj}$, and ϕ and Φ denote the standard normal density and cumulative distribution function respectively (Greene 2005).

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

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

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 (P_{ij}) can be sharpened using separating variables, but as Orea and Kumbhakar (2004) state, 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:

$$(6)\qquad LF_i = \sum_{j=1}^{J} P_{ij} LF_{ij}\ .$$

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

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

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:

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

This models each individual farm to be in the same group over time. Because of the unbalanced panel, not all farms are present each year.

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. The inputs are COWS, FEED, CAPITAL, LABOR, CROP, and OTHER. These 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. DBST1 takes the value of one if 25 percent or fewer of the cows were treated with bST sometime during their lactation; DBST2 takes the value of one if between 25 to 75 percent of the cows were treated with bST; and DBST3 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 estimated for parlor and stanchion farms are:

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

$$u_{it} = \exp\left(-\eta \cdot (\tau - T)\right) \cdot u_i,$$

where t is a time trend, *DLOC* are the regional dummies, and subscripts l and k are used for inputs, z for zones, and h for bST usage. The Battese and Coelli (1992) specification of the inefficiency term is used.

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

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

$$u_{it}\big|_j = \exp\left(-\eta\big|_j (\tau - T)\right) \cdot u_i\big|_j.$$

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 2004). Applying both AIC and SBIC separately leads to the conclusion that a model with two groups is the preferred model for these data.

Table 2 reports the estimation results of equations (9) and (10). All the first-order coefficients are positive and significant in all models. As ex-

[5] The New York counties in each defined region are as follows:

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

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

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

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

[6] The statistics can be written as:

$$AIC = -2 \cdot \log LF(J) + 2 \cdot m;\quad SBIC = -2 \cdot \log LF(J) + \log(n) \cdot m,$$

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.

Table 2. Stochastic Frontier Translog Production Function Estimates

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

pected, the Bovine Somatotropin dummies indicate that a higher use of this growth hormone increases production *ceteris paribus*. The same result was found in Cabrera, Solis, and del Corral (2010). Moreover, farms located in the East are the least productive farms, with 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 consistently good quality soils and is the region where many of the larger farms have evolved. The Northwest is the second most productive region after the Northeast.

Table 3 shows the averages of representative variables for the two groups obtained in the latent class model as well as for both milking systems, while Table 4 shows the number of farms in the sample for each group and each year. There are differences between parlor and stanchion farms, but greater differences appear to exist 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, additional characteristics appear important to differentiate the sample farms. A closer investigation of the estimated results of the production functions provides insights.

Output elasticities from the parlor and stanchion technologies 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 was rejected only for OTHER at the 99 percent confidence level (t-statistic -3.34) and for LABOR at the 95 percent confidence level (t-statistic 1.98). 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 for 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

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

where ε_l is the weighted average for all farms of the output elasticity of input l using as weights the posterior probabilities in the latent class model, and the average of the output elasticity of input l in the milking system estimates. That is, ε_l varies across inputs and groups (i.e., parlor, stanchion, group1, and group2). 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 is rather similar except for labor, but that the distribution of the marginal products of the latent class models groups is clearly differentiated for all inputs except labor. Especially telling is the marginal product (MP) 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 possibly to inferior genetics, poor disease detection and control, 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 be associated simply with management.

In contrast, the MP of purchased feed, which is measured in dollars of expenditures, is much

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

Table 4. Number of Farms per Year and Group

	Milking System		Latent Class Model	
	Parlor	Stanchion	Group 1	Group 2
1993	157	191	248	100
1994	159	160	225	94
1995	164	157	222	99
1996	154	148	203	99
1997	151	124	192	83
1998	194	122	217	99
1999	185	121	217	89
2000	177	111	195	93
2001	139	82	147	74
2002	145	70	156	59
2003	127	73	143	57
2004	134	59	142	51
Total	1,886	1,418	2,307	997

higher in latent group 2 than in 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. Although the distribution of MPs of capital for both 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

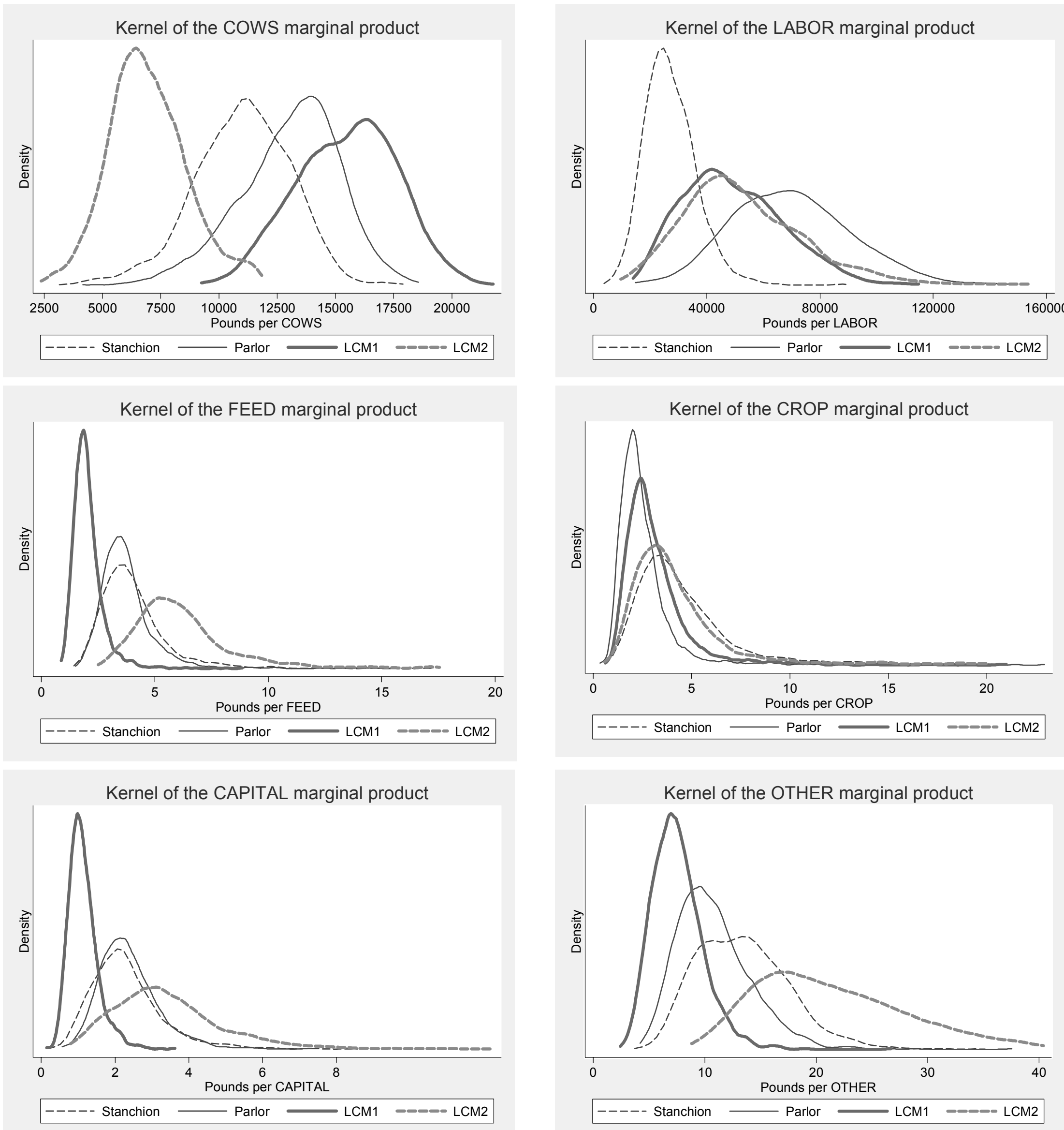

Figure 1. Kernel Distributions of the Marginal Products for All Groups

input, it appears that stanchion farms are similar to latent group 2, while parlor farms are similar to latent group 1. Finally, group 1 of the latent estimates displays technological progress, while group 2 does not.

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):

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

where the inefficiency term, u, is separated from the other error component using the formula developed by Jondrow et al. (1982).

The average technical efficiency in the parlor group was 0.89, whereas in the stanchion group it was 0.85 (Table 3). Thus, stanchion farms are less efficient on average than parlor farms. This difference was statistically significant based on a t-test (t-statistic 14.03). Note, however, that the efficiency of each group is measured with respect to a different frontier, and therefore the average efficiency is telling us which groups of farms are closer to their own frontier. 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 group 1 from the latent class model, implying that technical efficiency decreases over time for these two groups.[7] 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 that 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 in group 2, technical efficiency is higher for group 2 than group 1 in the last years of the sample.

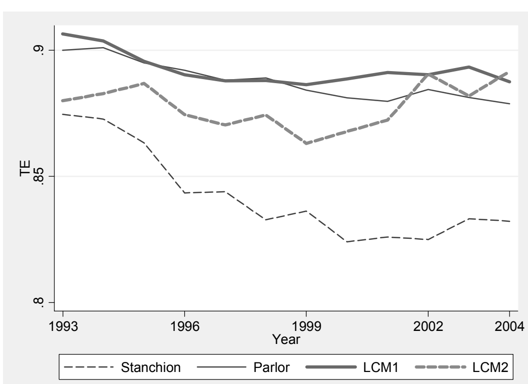

Figure 2. Average Technical Efficiency Over Time

[7] 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.

Conclusions

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 the 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 the kind of milking system as the separation criterion. Therefore, from a methodological point of view, we suggest that, if researchers suspect that farms in the sample do not share the same technological characteristics, they use latent class models to control for heterogeneity.

References

Ahmad, M., and B.E. Bravo-Ureta. 1995. "An Econometric Decomposition of Dairy Output Growth." *American Journal of Agricultural Economics* 77(4): 914–921.

Aigner, D., C.A.K. Lovell, and P. Schmidt. 1977. "Formulation and Estimation of Stochastic Frontier Production Function Models." *Journal of Econometrics* 6(1): 21– 37.

Alvarez, A., and J. del Corral. 2010. "Identifying Different Technologies Using a Latent Class Model: Extensive versus Intensive Dairy Farms." *European Review of Agricultural Economics* 37(2): 231–250.

Alvarez, A., J. del Corral, D. Solís, and J.A. Pérez. 2008. "Does Intensification Improve the Economic Efficiency of Dairy Farms?" *Journal of Dairy Science* 91(9): 3693–3698.

Amsler, C., Y.H. Lee, and P. Schmidt. 2009. "A Survey of Stochastic Frontier Models and Likely Future Developments." *Seoul Journal of Economics* 22(1): 5–27.

Bagi, F.S. 1984. "Stochastic Frontier Production Function and Farm-Level Technical Efficiency of Full-Time and Part-

Time Farms in West Tennessee." *North Central Journal of Agricultural Economics* 6(1): 48–55.

Balcombe, K., I. Fraser, M. Rahman, and L. Smith. 2007. "Examining the Technical Efficiency of Rice Producers in Bangladesh." *Journal of International Development* 19(1): 1–16.

Battese, G.E., and T.J. Coelli. 1992. "Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India." *Journal of Productivity Analysis* 3(1/2): 153–169.

Battese, G.E., S.J. Malik, and S. Broca. 1993. "Production Functions for Wheat Farmers in Selected Districts of Pakistan: An Application of a Stochastic Frontier Production Function with Time-Varying Inefficiency Effects." *The Pakistan Development Review* 32(3): 233–268.

Bravo-Ureta, B.E. 1986. "Technical Efficiency Measures for Dairy Farms Based on a Probabilistic Frontier Function Model." *Canadian Journal of Agricultural Economics* 34(3): 399–415.

Brümmer, B., T. Glauben, and G. Thijssen. 2002. "Decomposition of Productivity Growth Using Distance Functions: The Case of Dairy Farms in Three European Countries." *American Journal of Agricultural Economics* 84(3): 628–644.

Byma, J.P., and L.W. Tauer. 2010. "Exploring the Role of Managerial Ability in Influencing Dairy Farm Efficiency." *Agricultural and Resource Economics Review* 39(3): 505–516.

Cabrera, V.E., D. Solís, and J. del Corral. 2010. "Determinants of Technical Efficiency Among Dairy Farms in Wisconsin." *Journal of Dairy Science* 93(1): 387–393.

El-Osta, H.S., and M.J. Morehart. 2000. "Technology Adoption and Its Impact on Production Performance of Dairy Operations." *Review of Agricultural Economics* 22(2): 477–498.

Emvalomatis, G. 2012. "Productivity Growth in German Dairy Farming Using a Flexible Modelling Approach." *Journal of Agricultural Economics* 63(1): 83–101.

Fuwa, N., C. Edmonds, and P. Banik. 2007. "Are Small-Scale Rice Farmers in Eastern India Really Inefficient? Examining the Effects of Microtopography on Technical Efficiency Estimates." *Agricultural Economics* 36(3): 335–346.

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

____. 2008. "The Econometric Approach to Efficiency Analysis." In H. Fried, C.A.K. Lovell, and S. Schmidt, eds., *The Measurement of Productive Efficiency and Productivity Growth*. Oxford: Oxford University Press.

Hoch, I. 1962. "Estimation of Production Function Parameters Combining Time-Series and Cross-Section Data." *Econometrica* 30(1): 34–53.

Jondrow, J., C.A.K. Lovell, I.S. Materov, and P. Schmidt. 1982. "On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model." *Journal of Econometrics* 19(2/3): 233–238.

Knoblauch, W.A., L.D. Putnam, and J. Karszes. 2005. "Dairy Farm Management Business Summary New York State 2004." Research Bulletin No. 2005-03, Department of Applied Economics and Management, Cornell University, Ithaca, NY.

Kompas, T., and T.N. Che. 2006. "Technology Choice and Efficiency on Australian Dairy Farms." *Australian Journal of Agricultural and Resource Economics* 50(1): 65–83.

Kumbhakar, S.C., and C.A.K. Lovell. 2000. *Stochastic Frontier Analysis*. Cambridge, UK: Cambridge University Press.

Kumbhakar, S.C., E.G. Tsionas, and T. Sipiläinen. 2009. "Joint Estimation of Technology Choice and Technical Efficiency: An Application to Organic and Conventional Dairy Farming." *Journal of Productivity Analysis* 31(3): 151–161.

Moreira, V.H., and B.E. Bravo-Ureta. 2010. "Technical Efficiency and Metatechnology Ratios for Dairy Farms in Three Southern Cone Countries: A Stochastic Meta-Frontier Model." *Journal of Productivity Analysis* 33(1): 33–45.

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(2): 191–205.

Orea, L., and S. Kumbhakar. 2004. "Efficiency Measurement Using a Latent Class Stochastic Frontier Model." *Empirical Economics* 29(1): 169–183.

Sauer, J., and C.J. Morrison Paul. 2013. "The Empirical Identification of Heterogenous Technologies and Technical Change." *Applied Economics* 45(11): 1461–1479.

Tauer, L.W. 1993. "Short-Run and Long-Run Efficiencies of New York Dairy Farms." *Agricultural and Resource Economics Review* 22(1): 1–9.

____. 1998. "Cost of Production for Stanchion Versus Parlor Milking in New York." *Journal of Dairy Science* 81(2): 567–569.

Xu, X., and S.R. Jeffrey. 1998. "Efficiency and Technical Progress in Traditional and Modern Agriculture: Evidence from Rice Production in China." *Agricultural Economics* 18(2): 157–165.