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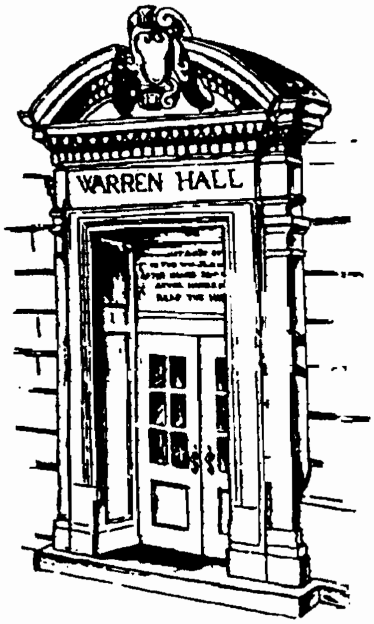

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EFFICIENCY, TECHNOLOGY, AND PRODUCTIVITY CHANGES ON INDIVIDUAL DAIRY FARMS

by

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Abstract

Individual technology and efficiency changes of 49 New York dairy farms were estimated using Malmquist indices. These were calculated using nonparametric mathematical programming methods, which place no functional form restriction on the technology, but since individual farm output is subject to stochastic events, a chance-constrained specification was used. Over a ten-year period, the average technical efficiency of these farms did not change, and technical change only averaged .2 percent. A comparison assuming deterministic output showed little difference in averages, but individual estimates varied.

Keywords

Technology, Efficiency, Productivity, Malmquist, Dairy

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EFFICIENCY, TECHNOLOGY, AND PRODUCTIVITY CHANGES ON INDIVIDUAL DAIRY FARMS

The dairy industry experienced dramatic changes during the last decade. As the federal government reduced its role in that sector, milk and input prices oscillated and new technologies were introduced. In such a competitive but dynamic market, the productivity of a farm over time is paramount for its success. Productivity changes, however, are comprised of two components. One is the shift outward of the technology set, the other is an increase in efficiency within that technology set. Previous estimates of agricultural productivity were not able to distinguish between these two components (Ball). The ability to distinguish is important since a farm can increase its productivity either by adopting new technologies or by more efficiently using old technologies. Although all farms must eventually adopt new technologies to expand their production set, many may find it advantageous to put more emphasis on efficiently using current technologies and wait to adopt new technologies.

Färe, Grosskopf, Norris and Zhang (1994) demonstrate a technique that allows the decomposition of productivity growth into two mutually exclusive and exhaustive components: changes in technical efficiency over time, and shifts in technology over time. Productivity growth is measured as a geometric mean of two Malmquist productivity indices, which, unlike the Tornquist index, does not presume an underlying functional form for technology. As such, they show how the index can be calculated using nonparametric programming methods, which place no functional form restriction on the technology. In addition, since the Malmquist is based upon distance functions, which do not require cost or revenue shares to aggregate inputs and outputs, there is no necessary underlying assumption that producers either minimize costs or maximize profits. It is strictly a primal approach to measuring total factor productivity. Färe et al. (1994) apply this technique to a sample of OECD countries over the period 1979-88. Other applications of this technique include Färe, Grosskopf, Lingren and Roos (1992), as well as Färe, Grosskopf, Yaisawarng and Wang (1990).

I use this technique with farm level data to measure the individual technology and efficiency changes of 49 New York dairy farms. Very few estimates of individual farm productivity are available, and none of these separate productivity into technology and efficiency components (Shoemaker and Somwaru). A limitation to applying the Färe et al. (1994) technique is that farm output is subject to random events such as weather, which can noticeably affect nonparametric results where observations are treated deterministically. To overcome that limitation, I modify the procedure of Färe et al. (1994), allowing the occurrence of stochastic output by the use of chance-constrained programming techniques (Land, Lovell and Thore). I compare results, treating output stochastically and deterministically. Finally, technology shifts and efficiency decreases are the underlying concepts in the adjustment cost theory of investment (Treadway). I test those concepts by regressing estimates of technology shifts and efficiency changes on individual firm investment.

Procedure

For each time period t=1,...,T, the technology set transforming inputs $x^t \in R^N_+$ into outputs $y^t \in R^M_+$ is defined as

$$s^t = \{(x^t, y^t): x^t \text{ can produce } y^t\}.$$

The output distance function is defined at time t as

$$(1) \qquad D_o^t(x^t, y^t) = \inf\{\theta: (x^t, y^t/\theta) \in s^t\} = \left(\sup\{\theta: (x^t, \theta y^t) \in s^t\}\right)^{-1}.$$

This essentially shows how much y can be increased given a quantity of x, such that x and θy remain in the production set. An input distance function can similarly be defined and under constant returns is reciprocal to the output distance function. An output rather than an input distance function is used since farmers probably try to increase their outputs given their use of inputs, rather than decrease inputs given their outputs.

To construct the Malmquist index, it is necessary to define distance functions with respect to two different time periods as

$$(2) \qquad D_o^t(x^{t+1}, y^{t+1}) = \inf\{\theta: (x^{t+1}, y^{t+1}/\theta) \in s^t\}$$

and

$$(3) \qquad D_o^{t+1}(x^t, y^t) = \inf\{\theta: (x^t, y^t/\theta) \in s^{t+1}\}.$$

The first distance function measures the maximal proportional change in outputs required to make (x^{t+1}, y^{t+1}) feasible in relation to the technology at time t. Similarly, the second distance function measures the maximal proportional change in output required to make (x^t, y^t) feasible in relation to the technology at time t+1.

Using these distance functions, Färe et al. (1994) then construct a Malmquist index. Of interest here is how they decompose that index into efficiency and technical changes as:

$$\text{efficiency change} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}$$

and

$$\text{technical change} = \left[\left(\frac{D_o^{\,t}(x^{t+1},y^{t+1})}{D_o^{\,t+1}(x^{t},y^{t})}\right) x \left(\frac{D_o^{\,t}(x^{t},y^{t})}{D_o^{\,t+1}(x^{t+1},y^{t+1})}\right)\right]^{\frac{1}{2}}.$$

The Malmquist index is the product of efficiency change and technical change.

The distance function itself measures efficiency, and thus the efficiency change measure is simply the ratio of two normal distance functions from two adjacent time periods. The technical change measure is the ratio of the distance function at time t using the netput vector at time t+1 (equation 2), to the distance function at time t+1 using the netput vector at time t (equation 3), measuring the output expansion that is possible. However, since some of that output expansion may be due to efficiency change, it is necessary to divide by the efficiency change, and then the geometric mean taken.

These defined distance functions are reciprocals to the output-based Farrell measure of technical efficiency and can be calculated for each firm using nonparametric programming techniques. The linear programming model to calculate output distance function (1) for each of the K firms for each time period t is:

(4) $\left(D_o^{\,t}(x^{k',t},y^{k',t})\right)^{-1} = \max \theta^{k'}$

subject to

(4.a) $\sum_{k=1}^{K} z^{k,t} y_m^{\,k,t} \geq \theta^{k'} y_m^{\,k',t}$ $\qquad m = 1,\ldots,M$

$\sum_{k=1}^{K} z^{k,t} x_n^{\,k,t} \leq x_n^{\,k',t}$ $\qquad n = 1,\ldots,N$

(4.b) $z^{k,t} \geq 0$ $\qquad k = 1,\ldots, K$

where z is the intensity vector. The technology specified here is nonparametric but assumes constant returns to scale and strong disposability of inputs and outputs.

If the outputs but not the inputs of the K firms are stochastic, then the constraint specified by equation (4.a) can be treated probablistically as:

$$(4.a)^* \quad P\left\{\sum_{k=1}^{K} z^{k,t} y_m^{k,t} \geq \theta^{k'} y_m^{k',t}\right\} \geq 1-\alpha_i \qquad m = 1,\ldots,M.$$

This simply states that the constraint must be satisfied 1-α_i of the time. Assuming that the distribution of $y_m^{k,t}$ is multivariate normal, and using a critical probability level of .05, equation (4.a)* of Problem (4) can be converted into its certain equivalent (Charnes and Cooper):

$$(4.a)' \quad \sum_{k=1}^{K} z^{k,t} E\{y_m^{k,t}\} - 1.645\left(\sum_{i=1}^{J}\sum_{j=1}^{J} \operatorname{cov}\left(y_m^{i,j} y_m^{i,j}\right)\mu^{k,t}\mu^{k,t}\right)^{.5} \geq \theta^{k'} E\{y^{k',t}\} \quad m = 1,\ldots,M$$

with $\mu^{k,t} = z^{k,t}$ for $k \neq k'$, and $\mu^{k,t} = \left(z^{k',t} - 1\right)$ for $k = k'$.

The change of variable and introduction of $\mu^{k,t}$ is necessary since the output of the k′th firm occurs twice in the constraint. Some chance-constrained efficiency examples can be found in Land, Lovell and Thore.

The nonparametric computation of $D_o^{t+1}\left(x^{k',t+1}, y^{k',t+1}\right)$ is exactly like (4), where t+1 is substituted for t. The two distance functions specified in equations (2) and (3) require firm data from adjacent periods. The first is computed for firm k as

$$(5) \qquad \left(D_o^{t}(x^{k',t+1}, y^{k',t+1})\right)^{-1} = \max \theta^{k'}$$

subject to

$$P\left\{\sum_{k=1}^{K} z^{k,t} y_m^{k,t} \geq \theta^{k'} y_m^{k',t+1}\right\} \geq 1-\alpha_i \qquad m = 1,\ldots,M$$

$$n = 1,\ldots,N$$

$$\sum_{k=1}^{K} z^{k,t} x_n^{k,t} \leq x_n^{k',t+1} \qquad k = 1,\ldots,K$$

$$\alpha_i = 0.05$$

$$z^{k,t} \geq 0$$

The second is specified as in (5), but the t and t+1 superscripts are transposed. Both are transformed into their certain equivalents.

Data

The data are from 49 New York dairy farms that participated in the New York Dairy Farm Business Summary for each year from 1977 through 1987. These 49 farms are surprisingly heterogeneous, located throughout the State, and range in size from 21 to 403 cows in 1987 (average, 118; standard deviation, 83). On average, they increased their cow herds by 36 percent over the 11-year period, although a few maintained their size. Milk production per cow averaged 15,573 pounds during 1987, which is greater than the state average of 13,920 pounds during that year. If high milk production per cow is a sign of good management, then these farms are well managed.

Six inputs and one output were defined. Although the procedure can handle any number of outputs, outputs other than milk, such as cull cows and excess grown feed, are by-products of milk production, and milk usually consists of about 85 to 90 percent of receipts. To maintain a low input/output dimension, these miscellaneous outputs were converted into a milk equivalent by dividing receipts by the farm price of milk. The six inputs (Table 1) were constructed by aggregating 28 separate expense items into one of the six inputs using a geometric average with individual firm cost shares for each input as weights. Unfortunately, this aggregation imposes functional structure and cost minimization behavior on the data, the absence of was the motivation for a nonparametric approach. However, aggregation of 28 measured inputs into a reduced set is necessary so that not every firm is measured as technical efficiency. Leibenstein and Maital state that given enough inputs all (or most) of the firms will be rated efficient, as a direct result of the dimensionality of the input/output space relative to the number of observations (firms).

After aggregation, expenditures and milk receipts were converted into quantities by dividing by annual published price indices (1977 = 100). This essentially converts all expenditures and receipts into 1977 dollars with the assumption that all farmers paid and received the same prices in any given year. In the sense that some individual farm expenditures were greater because of a higher price paid for a quality input (hired labor, as an example), then dividing by the same price for all farms converts these inputs into a quality-adjusted input, reflected as a larger quantity of a constant-quality input.

To apply the chance-constrained approach, it was necessary to formulate the expected output and variance/covariance of output. The simplest approach would be to take the actual production during a given year as expected output, and compute the variance/covariance matrix across the 49 firms using the 11 years of data. Since most farms displayed a general increase in output over the 11-year period, this would overstate variance. As an alternative, the variance/covariance matrix was estimated from the residuals around a linear trend line fitted for each of the 49 farms using actual output over the 11-year period as the dependent variable. As expected, the statistics from these regressions varied significantly, with a maximum R^2 value of .91, minimum of 0, and average of .45 (standard deviation was .28). It would also be possible to use the predicted value from the regressions as the expected output for any firm in a given year, but this would imply that any deviation from the trend was due to random error and none due to productivity. Thus, actual rather than forecasted values were used for the expected values of output. The coefficient of variation for the 49 farms averaged .12, with a minimum of .05 and a maximum of .26, computed from the square root of each farm's variance divided by the average output of each farm over the eleven years.

Productivity Results

The chance-constrained programs are nonlinear, and when using the covariance of output from 49 farms they become quite large. GAMS/MINOS was used to obtain solutions, and given that the problem was large and nonlinear, that software indicated that some of the obtained solutions may not be optimal. Rather than modify parameters of the MINOS solver, the covariance components of the programs first were dropped, and the models were run using only the variance of outputs. The correlation between the covariance solutions obtained and the counterpart variance solutions was .98, implying little accuracy was sacrificed using variance only. This may be due to the fact that the covariance values were low and almost half of the covariance terms were negative. This implies that there is no systematic factor affecting the randomness of output between farms. This may be because a common factor, such as weather, does not affect dairy production to the extent it impacts crop production. All of the results that follow are derived using only variance components of the 49 farms.

Since there are 11 years of data for 49 farms, 490 estimates of productivity, efficiency, and technical changes are generated. These are summarized in Table 2, which lists the geometric average for each of the 49 farms.

There is variation across farms. Farm #35 had the largest efficiency change average, at 5.3 percent (1.053), followed by farm #36 at a much lower 2.1 percent. Farm #48 had the lowest efficiency change average at -4.5 percent (.955). Twenty-seven of the 49 farms did not experience any change in their technical efficiency, while 10 increased their technical efficiency and 12 decreased their technical efficiency. On average, these farms did not experience any change in technical efficiency. That is as expected since technical efficiency is measured relative to the group.

Technical change averaged .3 percent over the 49 farms, with farm #39 having the largest at 9.6 percent, and farm #15 the second largest at 5.3 percent. Negative technical change was experienced by 27 farms, but of those, 22 still had indices over .98, implying that only 5 of the 49 farms experienced significant regressive technological change. Still, the fact that only 20 of the farms experienced positive technical change does not bode well for the future success of these dairy farms, and may partially explain why the number of dairy farms in New York decreased from 20,000 farms in 1978 to 14,500 farms in 1987.

Productivity change is the product of efficiency change and technical change. As such, farm #39, which had the highest technical change, experienced the largest productivity change average of 9.5 percent. Farm #35, which had the largest efficiency change, experienced the second largest productivity gain average of 2.9 percent. Farm #48, with the lowest efficiency gain, experienced the lowest average productivity gain of -5.8 percent. Only half of the farms experienced positive productivity change over this period.

Although the average productivity of the farms was low over this period, there were some years when the productivity increased significantly. As shown in Table 3, the greatest productivity change was 7.1 percent from 1979 to 1980, and the lowest was -.039 percent from 1986 to 1987. A previous estimate of New York dairy farm productivity from 1978 through 1982 was 6.6 percent (Shoemaker and Somwaru). Over that period the productivity of this group of dairy farms increased 8 percent.

Investment and Productivity Results

Previous attempts at explaining the efficiencies of New York Dairy Farm Business Summary farms generally have not been successful, with only about 10 percent of the variation explained (Tauer). This inability to explain inefficiencies has also been found for Pennsylvania dairy farms (Grisley and Mascarenhas), and New England dairy farms (Bravo-Ureta and Rieger). Thus, no attempt is made here to explain efficiencies as a function of the characteristics of these farms. However, what is being computed are temporal changes in individual farms' efficiency and technology, so an opportunity exists to relate these changes to investment changes made at the farm level.

Separating the productivity index into efficiency and technological change components allows isolating shifts in the production frontier from catching up to that frontier. At the firm level, this is synonymous with the adjustment cost model of the firm (Treadway). A firm makes an investment that shifts up the production function, but in the short run output is decreased because of learning. To test this concept, both efficiency and technological change components are regressed separately on investment changes at the farm level. Investment is measured as the percentage change in assets each year. Since many farms raise their own cows, this measure is much more inclusive than purchased assets. Also included as a dummy variable is whether the farm changed its barn/milking type during the year. This is a technological change but may also cause a reduction in efficiency as workers learn to use the new equipment. Also included is the percentage change in cow numbers as a measure of farm size change.

All three of these variables were regressed with the 490 efficiency observations and then on the technological change observations. The results are shown in Table 4. The signs are generally what is expected. An increase in assets and a change to a new barn type decreases efficiency. An increase in assets shifts the production set outward. However, the overall fit of the equations is low. A change in assets, cows, or the barn type explains very little of the efficiency and technological changes occurring on these dairy farms.

Deterministic Results

In this paper, output was treated as stochastic, and chance-constrained programming was used to compute indices rather than treating output deterministically. It was argued that farm output is subject to weather and other stochastic events that have nothing to do with efficiency or technology. The obvious question becomes: Is it worth the added effort? To provide some information to answer that question, the indices were also computed treating output deterministically. There are 490 observation for each index and the statistics are summarized in Table 5.

As expected, if one has numerous estimates then random error averages out. Over the 490 estimates, the mean efficiency estimate treating output stochastically was 0.999. The mean efficiency estimate treating output deterministically was similar at 1.001. The means for the stochastic and deterministic technology change variables were also similar, as were the productivity or Malmquist indices. However, there were differences in individual estimates. The correlation between the 490 estimates of stochastic efficiency change and deterministic efficiency change was only .76, and the correlation between stochastic and deterministic technology change was even lower at .72.

Random output events occur between farms in any year but are probably more significant between years. Since the efficiency measure compares distance function values between farms in any given year, but the technology measure uses distance functions from adjacent years, it is logical that the stochastic and deterministic technology estimates be less correlated than the stochastic and deterministic efficiency estimates. Note that, in contrast, the Malmquist deterministic and stochastic productivity estimates are highly correlated at .94. It appears that if one is interested in comparing individual estimates, especially technological change, then treating output as stochastic is important; in the long run, however, randomness averages out.

Summary and Conclusions

A technique that allows the decomposition of the Malmquist productivity index into the technology and efficiency components was used to compute the technology and efficiency change on 49 New York dairy farms over the period 1977-1987. Since the Malmquist index does not presume an underlying functional form, it was computed using nonparametric programming techniques. However, since individual farm output is subject to stochastic events unrelated to technology or efficiency, a chance-constrained specification was used.

The average technology change of the farms over the 10-year period was only 0.3 percent, while the average efficiency change was a negative .01 percent, indicating that most of the productivity increase of these farms was due to gains in technological change rather than efficiency. The overall productivity gain of the farms over the 10-year period was very low at 2 percent, although during the 5-year period of 1978 through 1982, their productivity increased 8 percent. Although very little of the variation was explained, investment increased output, but led to a decrease in efficiency.

When compared with estimates from a deterministic nonparametric model, the means and standard deviations from the stochastic model were similar, although individual estimates varied. The correlation between the stochastic and deterministic technology estimates was only .72. This implies that stochastic output needs to be modeled if individual estimates are needed, but random errors average out over a group of estimates.

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Table 1. Input and Output Variables Used to Measure Malmquist Indices

Variable	1977 Average* (Standard deviation)	1987 Average* (Standard deviation)
Labor	12,525	14,227
	(8,475)	(14,329)
Purchased feed	27,119	42,071
	(15,208)	(30,362)
Energy	3,295	3,769
	(1,954)	(2,688)
Inputs for livestock	4,117	4,735
	(5,241)	(3,796)
Inputs for crops	17,665	22,838
	(13,384)	(19,589)
Real estate input	10,720	16,561
	(9,124)	(13,896)
Milk output	84,673	117,612
	(52,861)	(86,099)

*All values in 1977 dollars (1977=100).

Table 2. Geometric Means of Efficiency, Technical, and Productivity Changes for 49 Dairy Farms Over 11 Years (Computed from Malmquist Chance-Constrained, Nonparametric Model)

Farm	Efficiency	Technical	Productivity
1	1.000	0.967	0.966
2	1.011	1.000	1.010
3	0.983	0.989	0.972
4	0.980	0.992	0.971
5	1.000	0.948	0.947
6	1.005	0.991	0.995
7	1.000	1.012	1.012
8	1.009	0.999	1.008
9	1.000	0.985	0.984
10	1.000	1.020	1.019
11	0.984	0.991	0.975
12	0.997	0.985	0.982
13	0.993	0.984	0.976
14	1.000	1.045	1.044
15	1.004	1.053	1.057
16	0.971	1.009	0.980
17	0.993	0.994	0.987
18	1.000	1.022	1.022
19	1.013	1.008	1.020
20	1.000	1.004	1.003
21	1.000	1.007	1.006
22	1.000	1.032	1.031
23	1.000	1.002	1.002
24	1.007	1.021	1.027
25	0.973	0.988	0.961
26	1.000	0.990	0.990
27	1.000	0.983	0.982
28	0.993	0.983	0.975
29	1.010	0.996	1.006
30	1.000	0.996	0.996
31	1.000	1.000	0.999
32	1.000	1.018	1.017
33	0.976	0.988	0.963
34	1.021	1.001	1.022

Table 2. Geometric Means of Efficiency, Technical, and Productivity Changes for 49 Dairy Farms Over 11 Years (Computed from Malmquist Chance-Constrained, Nonparametric Model) (cont.)

36	1.021	0.969	0.989
37	1.000	1.005	1.004
38	1.000	0.999	1.000
39	1.000	1.096	1.095
40	1.000	1.055	1.053
41	1.000	0.980	0.979
42	0.990	0.996	0.985
43	1.000	1.066	1.064
44	1.000	1.049	1.048
45	1.000	0.991	0.993
46	1.000	0.981	0.980
47	1.000	0.995	0.994
48	0.955	0.986	0.942
49	1.000	1.036	1.035
Geometric Mean	0.999	1.003	1.002

Table 3. Productivity Change by Year for 49 Dairy Farms (Geometric Means)

Year	Productivity Change
1977-78	0.964
1978-79	1.027
1979-80	1.071
1980-81	1.019
1981-82	0.966
1982-83	0.998
1983-84	0.969
1984-85	1.015
1985-86	1.024
1986-87	0.961

Table 4. Linear Regressions of Efficiency and Technological Changes on Farm Changes

	Efficiency	Technology
Constant	1.0087*	1.0049*
(T-statistic)	(162.48)	(124.34)
Asset change (percent)	-.0007*	.0011*
(T-statistic)	(-2.11)	(2.55)
Cow number change (percent)	.0014	.0011
(T-statistic)	(-1.91)	(1.19)
Barn change (dummy)	-.0650*	-.027
(T-statistic)	(-2.10)	(.67)
Adj. R	.02*	.01*
(F value)	(3.90)	(3.31)

*Statistically different from zero at .05.

Table 5. Comparison of Efficiency, Technological, and Productivity Changes Treating Output as Stochastic and Deterministic

	Geometric Mean
Deterministic efficiency	1.001
Stochastic technology	1.003
Deterministic technology	1.002
Stochastic productivity	1.002
Deterministic productivity	1.003
	Correlation with stochastic measure
Deterministic efficiency	.76
Deterministic technology	.72
Deterministic productivity	.94

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