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Scale efficiency in the New Zealand dairy industry: a non-parametric approach†

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The aim in this article is to measure the scale efficiency of the New Zealand dairy industry and to examine the relationship between farm size and technical efficiency. Data envelopment analysis (DEA) is applied to a sample of 264 dairy farms. The results suggest that 19 per cent of these farms are operating at optimal scale, 28 per cent at above optimal scale, and 53 per cent at below optimal scale. On average, the optimal size for New Zealand dairy farms is estimated at 83 hectares with a herd of 260 animals. Average technical efficiency is estimated at 89 per cent.

1. Introduction

In a recent paper, Jaforullah and Devlin (1996) point out that one of the more conspicuous outcomes in the New Zealand dairy farming sector in recent years has been an apparent acceleration in the long-term trend of increasing farm size. The average size of dairy farms increased from 79 hectares in 1980 to 89 hectares in 1990, and 107 hectares by 1995.[1]

Jaforullah and Devlin observe that this acceleration in the rate of increase in the size of dairy farms has coincided with moderate growth in returns to dairy farming as a result of more stable international prices for dairy products. They also point out that the industry has experienced increased optimism with the recent favourable GATT outcome. As a result, the industry is experiencing an increase in investment and in the number of farms. Large publicly listed companies (such as Tasman Agriculture and Applefields) are becoming involved in the industry, and the farms operated

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[1] Source: *New Zealand Official Yearbooks*, Statistics New Zealand, various years.

by these groups tend to be substantially larger than the traditional New Zealand farm.[2] Ownership of dairy farms by private (non-farmer) investors is also becoming increasingly common. In addition, as a result of the increasingly good outlook for the New Zealand dairy industry, sheep and beef farms, predominantly in the South Island, are being converted to dairy farms. Conversions were initiated in the Southland region in the late 1980s by the listed companies as a means of achieving substantial land holdings in the dairy industry. Individual owner-operators have also been converting farmland. As a result of the relatively low land prices in the Southland region, these converted farm units have often been 50 per cent larger than the traditional New Zealand dairy farm. Jaforullah and Devlin suggest that the number of conversions has been substantial, with an estimated 98 extra dairy farms in the Southland region in the 1992–93 and 1993–94 seasons. Since these conversions began, land prices in the region have doubled.

The aim in this article is to examine whether this noticeable trend towards increasing dairy farm size is improving the efficiency of New Zealand dairy production. Jaforullah and Devlin addressed the same question, utilising a parametric stochastic production frontier approach. Their analysis showed that there was no significant relationship between farm size and efficiency. However, their methodology failed to address the multi-product nature of dairy production. In this article we employ a non-parametric technique, data envelopment analysis (DEA), to examine the relationship between farm size and efficiency using the same database as Jaforullah and Devlin (1996).

In section 2, the role of DEA as a tool for benchmarking farm performance is discussed. Next, a detailed specification of the DEA methodology for measuring technical efficiency is provided. This is followed by a discussion of the limitations of DEA. The data and sources on which the present analysis is based are outlined in section 5. Then follows a discussion of the results and a comparison with the results of previous studies. Finally, the principal conclusions are discussed along with their implications for improving dairy farm management practices.

2. Benchmarking performance using data envelopment analysis

Benchmarking is a procedure for improving performance by identifying best practice, measuring performance against best practice and then forming

[2] In 1993 the 34 farms operated by Tasman Agriculture had an average herd size of over 350 milking cows, compared with the average New Zealand milking herd size of 170 cows (Tasman Agriculture Limited 1993). These are still relatively large farms. According to Cloutier and Rowley (1993), the milking herd size per farm in Quebec, Canada, ranged from 28 to 60 cows.

benchmarking partnerships between best-practice (peer) and non-best-practice enterprises so that the latter can identify and then eliminate their less efficient practices. DEA involves the application of mathematical programming techniques to construct a best-practice benchmark from the observed data on inputs and outputs. Typically, the best-practice benchmark represents an amalgam of the best practices of one or more farms.

DEA has been used extensively for benchmarking performance. Recently the Electricity Supply Association of Australia[3] used DEA to benchmark the performance of Australia's electricity supply industry. The Bureau of Industry Economics used DEA to benchmark the performance of the Australian telecommunications industry against world best-practice in telecommunications.[4] There have been numerous other applications of DEA for performance benchmarking overseas.[5]

In order to explain how the best-practice benchmark for a farm A is constructed, assume there is only one input X and one output Y. Further assume that farm B is using the least amount of X to produce a unit of Y. Farm B is the best-practice farm. Given data on input–output combinations of all farms, DEA will identify farm B as the benchmark for farm A. It is possible for farm A to improve its production efficiency, i.e. to reduce its input per unit of output by using the more efficient production and farm management practices of farm B. The technical efficiency of firm A is the ratio of farm B's input per unit of output to that of farm A. The technical inefficiency of farm A would be one minus this ratio. Technical efficiency and technical inefficiency are usually expressed in percentage terms. The technical inefficiency of farm A indicates the potential reduction in inputs that farm A can achieve by adopting the best production and/or management practices of farm B. Technical efficiency and technical inefficiency defined in this way are called input-oriented measures.[6] The technical efficiency of farm B is 100 per cent because the productivity performance of farm B cannot be improved in the context of the existing data set. Farm B therefore represents an achievable best-practice benchmark for farm A and the other farms in the data set.

[3] Electricity Supply Association of Australia Limited (1994).

[4] Bureau of Industry Economics (1992).

[5] A description of DEA and a summary of these applications can be found on the following and related websites: http://www.emp.pdx.edu/dea/homedea.html#DEA_Title and http://www.warwick.ac.uk/~bsrlu/findex.htm

[6] Input-oriented measures of technical inefficiency measure the potential reduction (savings) in inputs, holding outputs constant. Output-oriented measures of technical inefficiency measure the potential increase in output, holding inputs constant.

In the real world things are considerably more complicated than the situation depicted by the simple model outlined above. Dairy farms produce a wide range of outputs and also use a large number of inputs. Outputs include milk-fat, milk-solid and milk-protein products. Inputs used by them include land, labour, capital (buildings and farm machinery), the dairy herd, animal health and herd-testing services, pasture and feed supplements, and fertiliser. Other factors that have an impact on the relative efficiency of dairy farms include differences in soil types, managerial skill, animal genetics and climate. In such a context, DEA allows the measurement of technical efficiencies of individual dairy farms, taking account of all quantifiable variables. The resulting differences in individual farm efficiencies (i.e. inefficiencies) are then attributed to other variables not included in the analysis. These other variables fall into two groups, those that can be controlled and those environmental and stochastic variables that are outside the control of the individual farmer. The major controllable variable is the managerial expertise of the farmer. Environmental variables that are outside the control of the individual farmer include differences in geology, geography, and climate and other stochastic events that impact on farm productivity.

When many farms are included in a DEA analysis, each producing multiple outputs from multiple inputs, the benchmark of a farm will be made up of more than one farm unless the farm itself is a best-practice or efficient farm in producing all outputs. A dairy farm will not usually be best-practice in producing all outputs. Accordingly, the best-practice benchmark of a farm may include a number of farms that are best-practice in producing one or more outputs. In addition, because the input and output configuration of each farm will be unique, each will have a unique benchmark. Accordingly, DEA identifies the best-practice farms in the best-practice benchmark and calculates the relative contribution of each to the benchmark. This would enable non-best-practice or less efficient farms to identify their relevant benchmark partners. Under normal business practices, the former should then be able to identify and emulate the better practices of the latter and thereby eliminate the controllable sources of inefficiency.

3. Measurement of technical efficiency using data envelopment analysis

As was mentioned earlier, DEA is based on linear programming techniques. The use of linear programming to measure technical efficiency is usually attributed to Charnes, Cooper and Rhodes (1978) although others had applied linear programming techniques to input-based efficiency measurement in the late 1960s and early 1970s. DEA has been extended over the years. A more recent development by Fare, Grosskopf and Lovell (1985) has been the decomposition of technical efficiency into its scale and other components. In this article, the methodology of Fare *et al.* is used to measure the technical efficiency and the scale efficiency of New Zealand dairy farms.[7]

In order to obtain separate estimates of technical efficiency and scale efficiency, input-oriented technical efficiency measures satisfying three different types of scale behaviour are specified and applied to the data on New Zealand dairy farms. These are constant returns to scale (CRS), non-increasing returns to scale (NRS), and variable returns to scale (VRS). The three DEA linear programming exercises are specified below. Each linear programming exercise must be solved separately for each dairy farm in the database.

Let Y be an $(M \times N)$ matrix of outputs for New Zealand dairy farms with elements y_{ij} representing the ith output of the jth dairy farm. Let X be a $(P \times N)$ matrix of inputs with elements x_{kj} representing the kth input of the jth dairy farm and z an $(N \times 1)$ vector of weights to be defined. The vector y^j is the $(M \times 1)$ vector of outputs and x^j is the $(P \times 1)$ vector of inputs of the jth dairy farm.

The CRS input-oriented measure of technical efficiency for the jth New Zealand dairy farm is calculated as the solution to the following mathematical programming problem:

$$\begin{aligned} \lambda_c^j &= \min_{\lambda,z} \lambda \\ \text{s.t.} \quad & y^j \leq Yz \\ & Xz \leq \lambda x^j \\ & z \in R_+^N \end{aligned} \tag{1}$$

The scalar value λ represents a proportional reduction in all inputs such that $0 \leq \lambda \leq 1$, and λ_c^j is the minimising value of λ so that $\lambda_c^j \cdot x^j$ represents the vector of technically efficient inputs for the jth dairy farm.[8]

Maximum technical efficiency is achieved when λ_c^j is equal to unity. In other words, according to the DEA results, when λ_c^j is equal to unity, a farm is operating at best-practice and cannot, given the existing set of observations,

[7] Fare *et al.* (1985) break down the measure of technical efficiency into three components: a measure of scale efficiency, a measure of efficiency relating to input congestion, and a measure of pure technical or managerial efficiency. In the present study we assume that dairy farms are subject to strong input disposability (i.e. have no difficulty in disposing of excess inputs) and hence that there is no inefficiency due to input congestion.

[8] Note that λ_c^j represents the proportional reduction achievable for all inputs. It is possible that a greater proportional reduction may still be achieved for one or more of the inputs of the jth farm, in which case measured technical efficiency may involve some input slack.

improve on this performance.[9] When λ_c^j is less than unity, the DEA results imply that a farm is operating at below best-practice and can, given the existing set of observations, improve the productivity of its inputs by forming benchmarking partnerships and emulating the best practices of its best-practice reference set (peer group) of farms.

As mentioned earlier, the DEA constructs a unique best-practice benchmark for each farm. This benchmark is constructed for farm j from the vector z, the values of its elements are determined when the above linear programming problem is solved. The ith element z_i of the vector indicates the contribution of the ith farm to the best-practice benchmark of farm j. For instance, if $z_i = 0.2$, then it would imply that the best-practice benchmark of farm j included 20 per cent of farm i. As noted earlier, the benchmark of a farm can reflect the contributions of a number of farms. Only best-practice farms can contribute to the benchmarks of individual farms. This is because the performance of a non-best-practice farm can, by definition, be improved upon. Therefore, non-best-practice farms cannot be included in the resulting best-practice benchmark for farm j. This implies that the majority of the elements of the vector z will be zero. The non-zero elements (i.e. $z_i > 0$) show the composition of the best-practice benchmark (i.e. the peer group or the best-practice reference set).

The resulting measure of technical efficiency (λ_c^j) is usually called a measure of overall technical efficiency. This is because the residual, overall technical inefficiency, includes all sources of inefficiency both controllable and uncontrollable. The resulting estimate of overall technical inefficiency will include inefficiency due to the size of the farm (scale), inefficiency due to poor farm management as well as the effects of differences in soil quality, animal genetics, climate and other unspecified variables including errors in measurement. In order to separate out inefficiencies due to farm size and to identify optimal scale for dairy farms, two additional DEA exercises must be carried out.

The non-increasing returns to scale technical efficiency for the jth New Zealand dairy farm is calculated as the solution to the following mathematical programming problem:

[9] Note that technological progress or the addition of new data (dairy farms) may change the best-practice frontier. So even though a farm is identified as best-practice in one sample or in one time period, it may not necessarily be best-practice in another sample or time period. However, a farm that is identified as inefficient in the present sample will remain inefficient so long as the present sample remains a subset of all other samples that include the farm. The farm can, however, become efficient in subsequent time periods by improving its performance and by adapting relatively faster to technological change.

$$\begin{aligned} \lambda_n^j &= \min_{\lambda,z} \lambda \\ \text{s.t.} \quad & y^j \leq Yz \\ & Xz \leq \lambda x^j \\ & lz \leq 1 \\ & z \in R_+^N \end{aligned} \tag{2}$$

where l is a $(1 \times N)$ vector of ones.

Likewise, the variable returns to scale technical efficiency for the jth New Zealand dairy farm is calculated:

$$\begin{aligned} \lambda_v^j &= \min_{\lambda,z} \lambda \\ \text{s.t.} \quad & y^j \leq Yz \\ & Xz \leq \lambda x^j \\ & lz = 1 \\ & z \in R_+^N \end{aligned} \tag{3}$$

Given these three estimates of technical efficiency, the input-oriented scale efficiency measure for the jth farm is calculated as the ratio of overall technical efficiency to variable returns to scale technical efficiency:

$$S^j = \lambda_c^j / \lambda_v^j \tag{4}$$

If the value of the ratio is equal to unity (i.e. $S^j = 1$), then the dairy farm is scale-efficient. This means that the farm is operating at its optimum size and hence that the productivity of inputs cannot be improved by increasing or decreasing the size of the dairy farm.

If the value of the ratio is less than unity (i.e. $S^j < 1$), then the DEA results indicate that the farm is not operating at its optimum size. If $S^j < 1$ and $\lambda_c^j = \lambda_n^j$, then the DEA results suggest that scale inefficiency is due to increasing returns to scale. This means that by increasing the size of the dairy farm, the farmer can improve the productivity of inputs and thereby reduce unit costs. If $S^j < 1$ and $\lambda_c^j < \lambda_n^j$, then the DEA results suggest that scale inefficiency is due to decreasing returns to scale. This implies that the dairy farm is too big and that the farmer can improve the productivity of inputs and hence reduce unit costs by reducing the size of the farm.

Rearranging equation 4 implies that overall technical efficiency is the product of variable returns to scale technical efficiency and scale efficiency:

$$\lambda_c^j = \lambda_v^j \cdot S^j \tag{5}$$

λ_v^j is also called pure technical efficiency, i.e. the technical efficiency of the jth dairy farm net of inefficiencies due to scale.

From equation 5, it can be seen that there are two sources of technical inefficiency. The first is scale inefficiency $(1 - S^j)$. The second is pure technical inefficiency $(1 - \lambda_v^j)$. In the absence of environmental differences (i.e. differences in soil quality, animal genetics, climate and other unspecified variables) and errors in the measurement of inputs and outputs, pure technical inefficiency would reflect departures from best-practice farm management. The way to eliminate this latter source of inefficiency would be to form a benchmarking partnership with relevant best-practice farms with a view to identifying and then emulating their farm management practices.

The output of DEA therefore includes measures of each farm's scale efficiency, pure technical efficiency, overall technical efficiency and identification of its best-practice benchmark. The latter identifies potential benchmark partners along with their respective contributions to the best-practice benchmark.

4. Limitations of data envelopment analysis

One limitation of DEA is that it is difficult conceptually to separate the effects of uncontrollable environmental variables and measurement error from the effect of differences in farm management. Where the DEA results indicate the existence of pure technical inefficiency, one still has to examine the relevant best-practice partners (peer group) to ascertain whether the estimated pure technical inefficiency is wholly or partially attributable to the influence of environmental variables that are outside the control of farm management. However, if these environmental variables are measurable, it is possible to include them specifically in the DEA and thereby exclude their influence from the resulting estimate of pure technical inefficiency. This does not overcome the problem of measurement errors and other non-measurable stochastic variables having some influence on the resulting estimates of pure technical inefficiency.

One way of overcoming the above problem is to use a parametric approach. The main parametric methodology for estimating technical efficiency is the stochastic frontier methodology.[10] This is based on the assumption that part of the error involved in the statistical estimation of a production frontier is attributable to pure technical inefficiency and the other part is due to stochastic factors including measurement errors. In this way the methodology separates the influence of stochastic variables

[10] Kumbhakar, Biswas and Bailey (1989); Kumbhakar, Ghosh and McGuckin (1991); Battese and Coelli (1988) and Jaforullah and Devlin (1996) apply stochastic production function methodologies in studying dairy farms.

from resulting estimates of pure technical inefficiency. However, the stochastic frontier methodology requires that the farm production function, the stochastic error term and the inefficiency term be specified prior to estimation of technical efficiency. Second, while this methodology has recently been extended to multiple outputs, the statistical and analytical properties of multiple output stochastic production functions have yet to be established.[11] Further, Kalirajan and Obwona (1994) have extended the stochastic frontier methodology to measure input-specific efficiencies of individual farms. Nevertheless, their approach is not able to identify relevant benchmark partners for individual farms without further extension. This extended methodology has been used by Kalirajan and Salim (1997) and Kalirajan, Obwona and Zhao (1996) to study the effects of economic reforms on productive capacity realisation in Bangladesh and to break down total factor productivity growth in China's agriculture, respectively.

One advantage of the parametric stochastic frontier methodology over the non-parametric DEA methodology is that, where causal factors are quantifiable, hypotheses concerning differences in technical efficiency can be tested statistically. The DEA methodology, on the other hand, focuses on deriving results for individual dairy farms and therefore can be viewed as a potential tool for assisting farm management to improve overall technical efficiency rather than for testing behavioural hypotheses.

5. Data and sources

The data are based on a survey of factory-supplying dairy farmers conducted by the Livestock Improvement Corporation Limited in 1993 for the New Zealand Dairy Board. The sample was randomly selected from Board records. It initially comprised 452 dairy farms. However, 76 of these farmers failed to meet survey criteria (e.g. having at least 30 cows, separate accounts for, and deriving at least half of their gross income from, dairy operations), 82 farmers declined to participate in the survey, and a further 30 provided data that could not be used.[12] The remaining 264 farmers were considered to be reasonably representative of New Zealand dairy farmers although there was the possibility that non-respondents operated farms that were less technically efficient than the farms operated by respondents.

The information collected in the survey was farmer-specific, relating to all farms owned by each farmer. However, the farmer had to be an owner-

[11] Coelli and Perelman (1996).

[12] Livestock Improvement Corporation (1993).

Table 1 Descriptive statistics for the sample of 264 New Zealand dairy farms

Dairy farm outputs and inputs	Mean	Median	Standard deviation	Minimum	Maximum
Milk-fat (kg)	29159	25521	15122	4409	80001
Milk-solids (kg)	50677	44474	26016	7509	184998
Milk-protein (kg)	21518	18822	10952	3100	80001
Total area (hectares)	91	75	66	16	485
Total labour (hrs per week)	80	80	36	40	410
Total dairy herd	258	225	134	65	1066
Animal health and herd testing ($NZ)	9263	7978	5595	462	33537
Pasture and feed supplements ($NZ)	9347	7112	7982	0	50443
Fertilisers ($NZ)	12037	9629	11763	0	84931
Assets ($NZ)	359517	313232	301752	4456	2023623

operator (or 50/50 sharemilker)[13] to be surveyed. A farmer who owned two or more farms, and had a 50/50 sharemilker on one or more of these farms, would not have been surveyed since he did not own all the cows.

The survey contained comprehensive and disaggregated information on the characteristics of each farm, including details of land use, dairy herd, outputs, costs, revenue and assets. For the purposes of the present study, it was assumed that dairy farms produced three products: milk-fat, milk-solid and milk-protein, all measured in kilograms. It was also assumed that there were seven inputs: land (hectares); labour (hours); dairy cattle (number); expenditure ($) on animal health and herd-testing services; pasture and feed supplements; fertilisers; and capital (i.e. buildings and equipment). Data relating to these inputs and outputs are summarised in table 1.

6. Results

The DEA results for the New Zealand dairy farms are summarised in table 2. The average measure of overall technical efficiency is estimated at 83 per cent. As indicated above, the overall technical efficiency of a dairy farm is the product of its scale efficiency and its pure technical efficiency. Average scale efficiency is estimated at 94 per cent while average pure technical

[13] The 50/50-sharemilking agreement is the most common form of sharefarming contract in New Zealand dairy farming, under which the farmer and the sharemilker each receive 50 per cent of the revenue from milk sales. Under this arrangement, the sharemilker typically provides the dairy herd and some assets (such as tractors and farm bikes) and is responsible for all day-to-day farm operations. The farmer provides the farmland, buildings and plant, and participates in seasonal activity, such as hay and silage making.

Table 2 Technical and scale efficiency scores of New Zealand dairy farms

	Overall technical efficiency (%)	Scale efficiency (%)	Pure technical efficiency (%)
Average	83	94	89
Standard deviation	14	10	13
Minimum	39	45	42
No. of efficient farms	50	50	104

efficiency is estimated at 89 per cent. The average level of overall technical inefficiency for the New Zealand dairy farms is estimated at 17 per cent. This implies that the dairy farms can, on average, reduce their inputs by up to 17 per cent by operating at optimal scales and by eliminating pure technical inefficiencies through the adoption of the best practices of efficient dairy farms. As shown in figure 1, pure technical inefficiency accounts for 11 percentage points and scale inefficiency 6 percentage points of the overall technical inefficiency of New Zealand dairy farms.

The scale efficiency results are summarised in figure 2. The DEA results for the individual dairy farms suggest that, of the 264 dairy farms, 19 per cent or 50 farms are operating at their optimal scale, 28 per cent or 73 farms are operating above their optimal scale and 53 per cent or 141 farms are operating below their optimal scale.

The characteristics of each of these groups are summarised in table 3. It would appear that the largest increase in technical efficiency could be

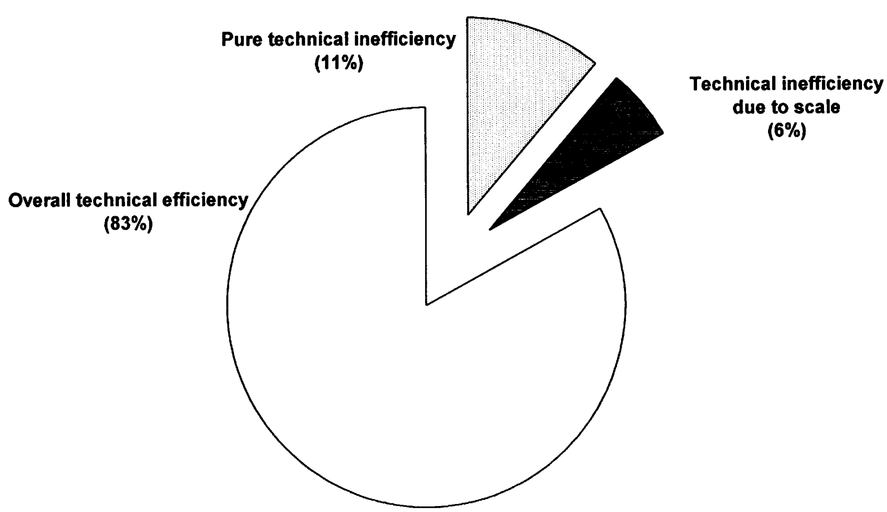

Figure 1 New Zealand dairy farms: efficiency of use of inputs

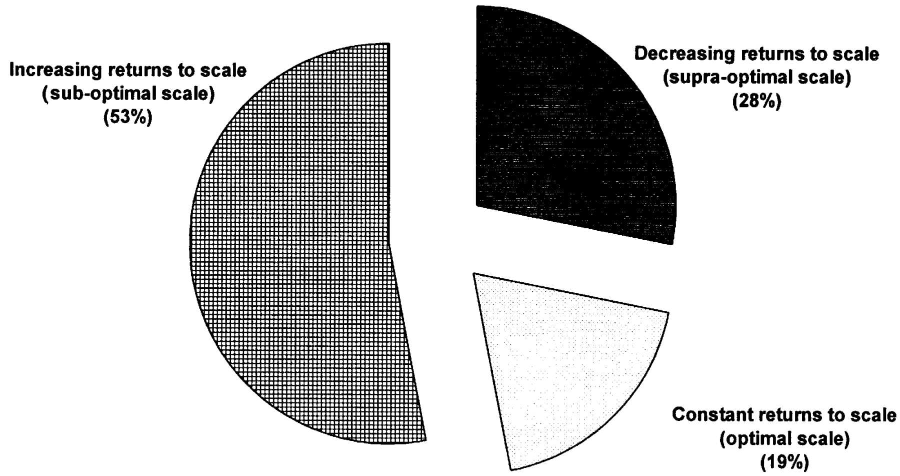

Figure 2 The scale efficiency of New Zealand dairy farms

achieved by addressing the problem of sub-optimal scale. Eliminating sub-optimal scale would increase the overall technical efficiency of 141 dairy farms by an average of 9 percentage points from 77 per cent to 86 per cent. Eliminating supra-optimal scale, on the other hand, would only increase the overall technical efficiency of 73 dairy farms by an average of 3 percentage points. This would suggest, from an agricultural policy viewpoint, that if production efficiency of the New Zealand dairy industry is to be improved, encouraging the trend towards larger farms would be better than discouraging this trend.

Table 3 Technical efficiency and scale of New Zealand dairy farms

Dairy farms	Optimal scale	Supra-optimal scale	Sub-optimal scale
Number	50	73	141
Area (ha)			
Average	83	135	70
Minimum	32	40	16
Maximum	253	485	252
Dairy herd (no.)			
Average	260	369	201
Minimum	115	132	65
Maximum	506	1066	542
Average measure of technical efficiency (%)			
Overall technical efficiency	100	84	77
Pure technical efficiency	100	87	86

On average, the optimal size of New Zealand dairy farms is estimated at 83 hectares with a dairy herd of 260 animals. The results summarised in table 3 suggest that the 141 dairy farms, referred to above, are below their optimal size by an average of 13 hectares and 59 animals. The results also suggest that 73 farms in the sample are above their optimal size by an average of 52 hectares and 109 animals while 50 farms are operating at optimal scale. It should be noted that DEA implies different optimal sizes for farms with different input–output configurations.

While the DEA results in general support a policy of encouraging increasing farm size, it would be better to use them to focus on efficiency improvement at the individual dairy farm level. From the literature, it can be deduced that there is a positive relationship between the availability of extension services and farm-level technical efficiency (Bravo-Ureta and Pinheiro 1997; Bravo-Ureta and Evenson 1994; Kalirajan 1991; Shapiro and Muller 1977). An increase in the rate of diffusion of technology and optimal farm management practices encouraged by extension services and programs should increase the technical efficiencies of the inefficient farms. The planning and design of these services and programs for the New Zealand dairy industry can benefit from the DEA results produced by the present study in several ways.[14]

First, dairy farm extension services providers can verify whether current extension programs are producing the expected results in terms of technical efficiency. They can do this by comparing the technical efficiencies of the farms using the extension services with those of others not using them. If the technical efficiencies of the former are higher than those of the latter, then this should confirm that the current extension programs are making dairy farms more efficient. These success stories can possibly be disseminated through field days to convince other farmers that they should also use the production/management practices recommended by dairy extension officers.

Second, the DEA results can be used by the dairy extension service providers to identify the best farm management practices for the dairy industry. This can be done through an examination of the farm management

[14] Livestock Improvement Corporation, a fully owned subsidiary of the New Zealand Dairy Board, is the main extension arm of the dairy industry. It has 34 consulting officers and 21 Farmwise consultants who provide information and support to dairy farmers on issues which affect dairy farm management and profitability. The consulting officer service has been based on a 'mass extension' approach via discussion groups and field days. Consulting officers have some individual contact with dairy farmers, but not on a regular/repeat basis. The Farmwise consultants are experienced farm management consultants who offer solutions to individual farmers on a user pays basis. From solving one-off problems to regular farm visits, these consultants are skilled in all aspects of dairy farming and dairy farm business management.

practices of the farms identified as technically efficient (frontier) by the DEA results. The identified best practices in farm management can then be documented and disseminated through various extension techniques such as mass media approaches, group activities and individual visits. However, for DEA to be useful as an extension tool in this respect, the production frontier, and consequently the set of frontier farms, should not change substantially during the period in question.

Third, using the DEA results, the most inefficient dairy farms can easily be identified. By studying the management practices of this group of farms, the dairy extension agents can detect the problems preventing these farms from achieving full efficiency. The DEA results can also be useful to a farm extension worker giving advice to farmers on a one-to-one basis on how to improve technical efficiency. Best-practice peers for the inefficient farms have been identified in this study, but not reported in this article. An extension worker familiar with the characteristics of the farms may study each inefficient farm and its benchmark peers to work out why the inefficient farm has failed to achieve full technical efficiency. If it is inefficient because of the use of inappropriate old technology, then technical advice and information should be made available to the farmer. If inefficiency is due to inexperience in farming, then training or facilitation of links with more efficient peers through a discussion group would be appropriate. As Fraser and Cordina (1999, p. 269) state, 'It is all very well having best practice described by an extension officer on a farm visit, but being able to observe directly best-practice farming techniques will enhance the learning experience.'

The DEA results relating to scale efficiency can also be useful to a farm extension worker. DEA determines whether a particular farm is scale efficient or not. Further, in the event of scale inefficiency, it determines whether the farm is sub-optimal or supra-optimal. Although the present article reports an average optimal size for the NZ dairy industry, we do not suggest that all farms should strive to achieve that size. In order to improve overall technical efficiency in the industry, each farm should be looked at individually. If a farm is optimal in size, nothing is to be done. If it is sub-optimal or supra-optimal, this information should be passed on to the farmer along with information on potential improvement in input productivity or potential savings in unit costs it can achieve by making the farm optimal in size. A farm extension worker may help the farmer in question achieve the optimal size.

The discussion above shows the potential uses of the DEA results to the dairy extension services providers. However, whether actual use of the results will lead to improvement in technical and scale efficiencies in the New Zealand dairy industry could not be demonstrated because of lack of data.

7. Comparison with other studies

Most previous studies of the efficiency of dairy farms have made use of the parametric stochastic frontier methodology. Moreover, these studies have not examined dairy farm efficiency based on multiple outputs as demonstrated in this study. Therefore, the studies that may be compared with the present one are few in number. These include Jaforullah and Devlin (1996), Cloutier and Rowley (1993) and Fraser and Cordina (1999). Of these, the latter two used DEA while the former used a stochastic production frontier approach to study technical efficiencies of dairy farms. Although Tauer (1998) used DEA to study the New York dairy farms, the results of that study are not comparable with the results of the present study because the type of data and methodology used in that study differ from that used in the present study. To break down productivity changes of the dairy farms, Tauer utilised panel data and DEA first to calculate Malmquist productivity indices for the farms and these were then broken down into technical change and efficiency change components. A similar methodology was used by Arnade (1998) to break down agricultural productivity changes in 70 countries into technical efficiency change and technical change components.

Jaforullah and Devlin (1996) utilised a number of different specifications of the stochastic production frontier and the same set of data in their examination of the relationship between technical efficiency and farm size. However, their measure of dairy farm output is the total revenue (NZ$) of the dairy farm whereas the measure of output used in the present study is the physical quantities of each of three dairy products. Their inputs are the same as in the present study. They report that there was no significant difference in average technical efficiency levels of large, medium and small farms. They also concluded on the basis of their statistical results that New Zealand dairy farming is characterised by constant returns to scale.

The DEA results reported in the present study do not contradict the statistical results of Jaforullah and Devlin (1996). DEA, being a non-parametric procedure, cannot be used to test hypotheses statistically. The DEA procedure focuses on individual farms. When aggregated over all farms, the DEA results reported in this article suggest that New Zealand dairy farms may be able to increase their technical efficiency by an average of 6 percentage points by moving to optimal scale. More specifically, the DEA results suggest that more than half the dairy farms are operating at below their optimal scale. These farms could increase their technical efficiency (i.e. increase the productivity of their inputs) by increasing farm size. The DEA results also suggest that there are a smaller number of farms that could increase their technical efficiency by reducing their size. In other words, the results presented in this article suggest that economies of scale exist for some farms, diseconomies for other farms.

Cloutier and Rowley (1993) applied DEA to measure the technical efficiency of 187 dairy farms in Quebec for the years 1988 and 1989.[15] They used three measures of output, milk (litres), revenue from the sale of milk (C$) and other revenue (C$). Inputs were cows, labour, land (hectares), animal feed and a composite of other inputs. Their DEA model was based on the assumption of constant returns to scale so that their resulting estimates of technical efficiency are comparable with the estimates of overall technical efficiency presented here. Their resulting estimates of average overall technical efficiency for the sample of Quebec dairy farms were 88 and 91 per cent for 1988 and 1989, respectively. These estimates of overall technical efficiency are somewhat higher than the estimate of 83 per cent obtained in the present study. Cloutier and Rowley report that 15 and 21 per cent of the dairy farms were efficient in 1988 and 1989, respectively, compared with 19 per cent in the present study. Their minimum scores on overall technical efficiency were 66 and 68 per cent, respectively, compared with 39 per cent in the present study.

In general, the DEA results reported by Cloutier and Rowley are similar to those reported in the present article in respect of the spread of overall technical efficiency scores, despite the fact that the Quebec dairy herds are very much smaller than the New Zealand dairy herds. The former range from 28 to 60 cows compared with the average New Zealand herd size of 258 animals. Cloutier and Rowley report, as in the present study, that most of the dairy farms in the sample have levels of overall technical efficiency that are close or equal to best-practice efficiency. They also note that the value of the DEA methodology lies in its focus on individual dairy farms and its potential usefulness as an integral part of an industry-oriented program to improve overall efficiency.

Fraser and Cordina (1999) used DEA to assess technical efficiency of 50 irrigated farms in Northern Victoria, Australia, for 1994–95 and 1995–96. They used one output and six inputs in their models and calculated the technical efficiencies of the dairy farms for the two years separately. Average technical efficiency of the farms was found to be 90.5 per cent in 1994–95 and 90.8 per cent in 1995–96. These estimates, although not strictly comparable, are very close to the estimate of 89 per cent in the present study.

[15] Cloutier and Rowley (1993) solve the multiplier form of the DEA linear programming problem. Using the duality in linear programming, the equivalent *envelopment* form of this problem can be derived. The envelopment form, which is specified in the present article, involves fewer constraints than the multiplier form and hence is usually the preferred form to use.

8. Conclusion

The primary objectives in this article have been to measure the scale efficiency of the New Zealand dairy industry and to examine the relationship between farm size and efficiency using non-parametric data envelopment analysis (DEA). As the study proceeded, another objective emerged. This was to show that DEA could be a useful tool for benchmarking farm performance by identifying best practice in dairy farm management. It is also proposed that DEA could form the basis for an ongoing program of performance improvement by identifying potential benchmark partners for the less efficient farms.

Accordingly, DEA has been applied to measure the overall technical efficiency, scale efficiency and pure technical efficiency of a sample of 264 New Zealand dairy farms. The results suggest that the average overall technical inefficiency of these farms is 17 per cent of which 6 percentage points are due to scale inefficiency and 11 percentage points are due to pure technical inefficiency. The DEA results suggest that by eliminating scale inefficiency and pure technical inefficiency, the New Zealand dairy industry could reduce inputs by 17 per cent with unchanged output.

In relation to scale efficiency, the DEA results suggest that, from an agricultural policy viewpoint, the trend towards larger farm sizes could have a beneficial impact on the efficiency of the New Zealand dairy farm industry as a whole. However, the conclusions vary at the individual farm level with 53 per cent of farms operating below their optimal scale, 28 per cent above optimal scale and 19 per cent at optimal scale. The DEA results indicate that optimal size varies depending upon each farm's particular input–output configuration. Accordingly, the DEA results for each farm should be examined to determine whether it is already operating at its optimal scale or whether the productivity of inputs can be increased through moving to optimal scale.

Likewise, the DEA results for individual farms can be examined to identify the scope for reducing pure technical inefficiency (i.e. poor farm management practices). The key DEA results for each firm include a measure of its optimal scale, its pure technical inefficiency and identification of potential benchmark partners (relevant efficient farms). By forming benchmarking partnerships and emulating the best practices of relevant efficient farms, less efficient dairy farms could eliminate pure technical inefficiency.

The strengths of the non-parametric DEA methodology are that it focuses on individual farms and it can be used by extension services agents as a potential vehicle for promoting the diffusion of best practices in farm management throughout the dairy industry. DEA is increasingly being used as a benchmarking tool in other industries and throughout the world. In

Australia, the government has introduced benchmarking as a means of stimulating microeconomic reform. Although other techniques, including the parametric stochastic production frontier estimation methodology, have been applied to estimate farm efficiency, these are currently unable to provide the same level of details on individual farms as the DEA methodology.

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