An application of Malmquist productivity index to compare technological and growth differences between traditional and non-traditional dairy regions in New Zealand

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Abstract

The NZ dairy industry has adopted an encompassing measure of performance, total factor productivity (TFP), as a target measure to guide on-farm improvements.

Dairy farmers pay a levy in order to fund agricultural research and extension. Extension services and R&D will continue to be of critical importance to maintain and improve productivity at the farm level. Consequently, it is in the best interest of the dairy industry to adequately target R&D and extension funds and make the best use of resources.

To date, the methodology employed to estimate productivity growth has some shortcomings that seriously hamper the ability of potential users to extract useful information from it. First, productivity growth has been reported as an aggregate for the entire dairy industry. Second, it makes no assumption about the efficiency with which resources are being used. Third, it implicitly assumes that all farms face the same technology.

Productivity growth can be achieved either through better (more efficient) use of the technology applied, through the adoption of a new technology (technical progress) or a combination of both. Given that the sources of productivity change—technical progress and technical efficiency change—are fundamentally different phenomena, they are, in turn, influenced by different factors. This distinction is important for policy orientation because different instruments/tools may be required to address them. Furthermore, empirical evidence suggests that a variety of farming systems have emerged as a result of dairy farming geographical expansion.

Farm-level panel data were used to estimate the Malmquist productivity change index. This index can provide additional insights since it can be decomposed into two additional components, one that measures changes in technical efficiency (i.e., whether firms are getting closer to the production frontier over time), and one that measures changes in technology (i.e., whether the production frontier is moving outwards over time). Hence, it provides individual (farm) estimates of TFP. Moreover, the methodology applied allows to test whether farms in the two regions considered in this study are operating under the same

technology. These two regions were the long-established dairy areas of Waikato-Taranaki and the newly developed dairy areas of Canterbury-Southland.

Results for farms in Waikato-Taranaki indicate that annual TFP change is modest, ranging from 0.29% per annum to 0.59% per annum. Most importantly, technical progress is the only source of TFP change in all four models. Therefore, it is necessary to encourage investments in new R&D targeted to remove the technological constraints that impede the realisation of further productivity gains in the regions. However, important differences in the estimates of TFP, technical progress and change in technical efficiency between models were found for farms in Canterbury-Southland. Estimates of TFP change ranged from 0.7% per annum to 2.8% per annum. Even though technical progress and change in technical efficiency contributed to total factor productivity growth (TFPG), the latter component was the most important contributor in three of the four models. Moreover, in two models the rate of technical progress was negative (i.e., technical regress).

The analyses indicate that dairy farms in Canterbury-Southland were on average 10% more productive than farms in Waikato-Taranaki when farms in both regions faced the frontier. These results were consistent for all the input/output set chosen. Furthermore, the null hypothesis that the two regions do not face the same production technology (i.e., each region has it own production frontier) was accepted irrespective of the input/output set chosen. The rejection of the null hypothesis, that farms in traditional and non-traditional dairy regions were operating under the same underlying technology (and hence face the same production frontier), called for a review of the traditional approach to R&D in one central experimental station, strengthening the need for a local approach through the promotion of networks and synergies with universities and other research institutions.

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CHAPTER 1

1 Introduction to the dairy industry and dairy farming in New Zealand

1.1 Background

The dairy industry is the most important agricultural industry in NZ, contributing around 3.2% to NZ's GDP (MAF, 2005). It is also the largest export industry, with export sales of processed milk and manufactured dairy products at $5.7 billion for the year ended June 2005. This represented approximately one-fifth of all NZ exports (MAF, 2005).

Total area devoted to dairy is 1.4 million hectares (LIC, 2005), accounting for less than 10% of the area occupied by grassland, arable cropland, horticulture and forestry. According the 2001 census, dairy farming is the main occupation for 26,331 people. This is around 20% of primary agricultural industry's employment population.

NZ accounts for 3% of world milk production. At the same time, it exports over 80% of its milk production. Given that only 7% of total dairy production is traded internationally, NZ is a key player in international dairy markets, contributing 40% of total traded dairy products.

NZ dairy production growth has been driven by improvements in farm and factory management and innovation, expansion and intensification of dairy farming and continued industry investment and restructuring.

While NZ milk producers and processors exhibit strengths in developing and marketing differentiated dairy products, they also strongly compete in dairy commodity markets (Dobson, 1996). The latter competitive strength stems partly from production efficiencies. At the farm level, production costs are among the lowest in the world (Holmes, 2003). Dairy processing plants tend to be large and operate efficiently during months of high milk production. However, the plants encounter inefficiencies because of the sharp reduction in milk throughput in the winter months (Holmes, 2003), offsetting some of the advantage they obtain from having access to low-cost milk (Dobson, 1996).

The low cost of the raw material has become a core competitive advantage as well as a source of value (Mountfort, 2002). However, this major source of competitive advantage will fade as other competitors can also achieve low production costs by increasing the scale and scope of production or by adopting a superior technology that drives down production costs (e.g., new, more persistent pastures with higher production).

The last two decades have witnessed profound changes to the internal and external environment in which the NZ dairy industry operates. These changes range from socio-institutional and political to productive.

Undoubtedly, the most important domestic change was the deregulation of the NZ economy in the 1980s that impinged on the relative profitability of agricultural industries, generating both the conditions for restructuring within the agricultural sector and the consequent changes in productive practices. (A comprehensive overview of NZ's economic reforms can be found in Evans, Grimes, Wilkinson and Teece (1996) and Silverstone, Bollard and Lattimore (1996) and its implications to agriculture in Blandford and Dewbre (1994), Frengley and Engelbrecht (1998), Johnson, Sandrey and Scobie (1994) and Warren and Frengley (1994).)

Changes in the international environment can be traced back to the developments of the Uruguay Round (UR) Agreement of the General Agreement on Tariffs and Trade (GATT), the liberalisation of trade, the re-organisation of dairy policies in developed countries aimed at reducing domestic support and the creation of the World Trade Organisation.

MAF International Policy (2002) estimated that without the UR, lower world prices for all four dairy products (butter, cheese, WMP, SMP) would have caused a decline in the overall export revenue generated from dairy exports of $346.6 million for the year 2000.

Among the new set of rules, special emphasis was put on the obligation of member countries to ensure that the activities of the State Trading Enterprises (STEs), referred to in paragraph 1 of Article XVII of GATT 1994, are consistent with the general principles of non-discriminatory treatment prescribed in GATT 1994 for governmental measures affecting imports or exports by private traders (WTO). Following this, the interpretation of Article XVII was agreed upon, and in order to ensure the transparency of the activities of STEs, member countries shall name such enterprises. Additionally, the understanding provides a working definition of STEs:

> Governmental and non-governmental enterprises, including marketing boards, which have been granted exclusive or special rights or privileges, including statutory or constitutional powers, in the exercise of which they influence through their purchases or sales the level or direction of imports or exports. (WTO)

Finally, it is worth mentioning that following the end of the UR, a worldwide wave of dairy industry consolidation took place (Zwanenberg, 2001). Zwanenberg (2001) identified some key driving forces behind the international consolidation of the dairy industry: growing demand for dairy products and increasing number of requirements from the consumer; increasingly powerful customers; milk supply growing more slowly than demand for dairy products and dairy politics (i.e., further developments of the WTO Rounds and EU enlargement).

The consequences that such changes—domestic or international, policy or business driven—had, and still have, on the NZ dairy industry are clearly intertwined, making isolation of the effects difficult. A detailed review of its effects is well beyond the scope of this dissertation. However, some of the main events will be outlined, as they are relevant to an understanding of the recent evolution of the NZ dairy industry and the thoughts that gave rise to this work.

1.2 Institutional changes

The last two decades have witnessed a profound alteration of the internal and external environment for the NZ dairy sector. Over the years, and particularly beginning in the early 1980s, the New Zealand Dairy Board (NZDB) evolved into a multinational dairy product firm, with active presence in more than twenty countries. As part of the economic reforms that began in the mid-eighties, the Board was divested of subsidies. However, it retained the statutory authority to be the single exporter of NZ's manufactured dairy products. It has been recognised (Dobson, 1998; Frampton, 2002 and Zwanenberg, 2001) that the statutory single exporter figure has contributed to the isolation of NZ from international takeovers. However, major changes have occurred inside its boundaries. An active process of mergers and acquisitions took place between the manufacturing cooperatives. The number of companies (cooperatives) has been reduced to four at the beginning of 2000, from sixteen in 1996, and thirty in 1980 (Holmes, 2003).

Frampton (2002) gives a brief and concise review of the developments that occurred during the 1990s that were crucial in creating the NZ dairy industry as it exists today. (For a comprehensive review of international and domestic developments, see Dobson, 1998.) Following the corporatisation of the NZDB by dairy companies (to secure farm ownership of the Board's assets) the larger shareholders demanded more efficiency (Dobson, 1998 and Frampton, 2002). After a first study that suggested $250 million could be obtained from improvements in performance, McKinsey & Co. was commissioned by the dairy industry to undertake two studies. The first, in 1997, recommended options on how to get those efficiency gains, while the second, in 1999, developed a strategy for the dairy industry to decide the preferred structure. The final proposal signalled that a single company, incorporating the NZDB, should be adopted.

The regulatory environment in which NZ farms operate changed with the approval of the Dairy Restructuring Act in 2001. The act allowed the merger of Kiwi and the New Zealand Dairy Group into a single company incorporating the New Zealand Dairy Board, thus creating a new cooperative called Fonterra.

Some of the main ideas behind the consolidation were[1]:

- Efficiencies of transport
- Economies of scale
- To reduce personnel
- To ensure New Zealanders, and not foreign customers, will take the benefits of those gains
- To retain/gain market share and market power

[1] Fonterra Cooperative Group. Annual Report 2001-02

Open letter to the shareholders of New Zealand Dairy Group and Kiwi Co-operative Dairies (13 June 2001),

John Roadley, Henry van der Heyden, Greg Gent. Dairy Industry letter to the Ministry about the Merger Package (5 January 2001)

- To strengthen their innovative capacity
- To improve their access to capital
- To secure milk supply

Even though Fonterra dominates the scene, two other cooperatives, Westland and Tatua, as well as many other smaller businesses, complement NZ's dairy industry.

Prior to the signature of the merger agreement, the Dairy Industry commissioned different studies in regard to the strategies to follow. Anderson and Johnson (2002) point out that the McKinsey Report (one of the studies commissioned) on the dairy industry identified the sluggish growth in on-farm productivity as an issue of concern.

Declining on-farm productivity and the prospect of losing competitive advantage, given developments in other dairy-exporting countries, induced the NZDB to establish Dexcel with the sole objective of helping farmers achieve on-farm productivity improvements through research, extension and education for dairy farmers (Pringle, 2000 and 2002). A(n) (aspirational) target of 4% per annum increase was identified as "critical to ensuring the future growth and vitality of the dairy industry" (Bodeker and Anderson, 2001 and Pringle, 2000). Funding was initially provided by the Board, and later, by a direct levy on all bovine milk producers. Levies are collected by dairy companies on behalf of their farmer suppliers and passed onto Dairy InSight, the agency responsible for the promotion and funding of dairy industry-good activities.

1.3 Dairy farming expansion

"Conversions" from sheep and beef units into dairy were a conspicuous feature of the years that followed the 1984 economic reforms (Jaforullah and Devlin, 1996; Johnston and Frengley, 1994 and Sandrey and Scobie, 1994). Bockstael (1996) affirmed that public policies might have a strong influence on the spatial pattern and distribution of land. The radical plan of economic reform, which included changes in monetary policy, fiscal policy and commercial policy, definitively modified business expectations, as resource allocation was to be determined by market forces (Johnson, 2000; Johnston and Frengley, 1994; Sandrey, 1991 and Sandrey and Scobie, 1994). The relative profitability of different agricultural industries was altered after deregulation, and as a result, the pattern of land use changed. The process of economic deregulation was one factor, amid others, that had an influence on the expansion of dairy farming into new areas. Other factors may also have played roles in promoting conversions. Johnson (2000) mentioned the problems in the international wool market following the failure of the Australian Wool Board support scheme in 1991. Additionally, Jaforullah and Devlin (1996) highlighted the importance of the favourable outcome of the GATT/WTO Uruguay Round of trade negotiations.

Prior to deregulation, wool and lamb production enjoyed a higher level of support than other agricultural economic activities, thereby encouraging sheep production (Johnston and Frengley, 1994 and Morrison et al., 2000). Morrison et al. (2000) provided evidence of the policy-induced changes in North Island Hill Country farms. They found changes in output composition as the production of beef and deer increased relative to wool and especially lamb. Johnson (2000) and Johnston and Frengley (1994) pointed out that, following deregulation, sheep production was displaced by dairy and, where suitable, forestry. In the same vein, Ruaniyar and Parker (1999) observed that even in the presence of substantial development costs, conversions from sheep and beef farming into dairy were common. Kilsby et al. (1998), studying the cost of conversion for five farms in the North Island, reported values ranging from $1,894 per hectare to $6,188 per hectare. In four cases, dairy shed and building costs accounted for the majority of the total cost.

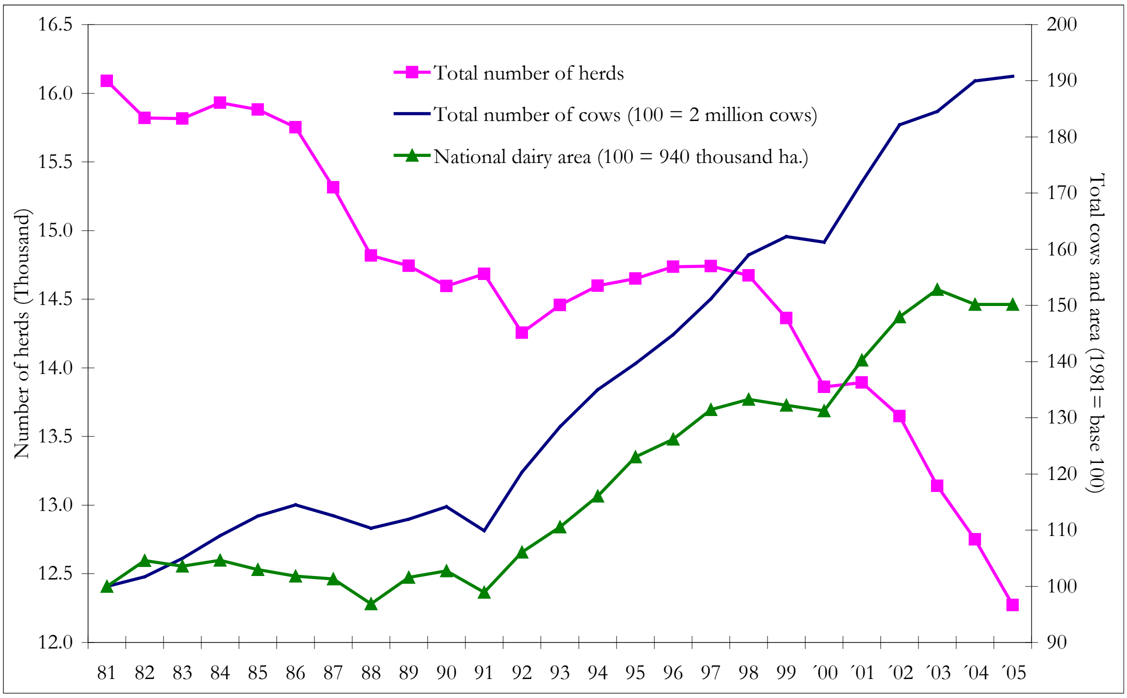
Jaforullah and Devlin (1996), and Jaforullah and Whiteman (1999) recognised that hand in hand with the increase in the number of dairy farms, the rate of growth in average farm size also accelerated. Supported by evidence from the Southland region, they identified two factors behind the increases in farm size, namely, the involvement of publicly-listed companies in dairy farming and "conversions" of sheep and beef owner-operators into new dairy farms. They stated that these new land holdings and herds were typically larger than the existing "average" dairy farm. According to the researchers, corporate farms entering dairy production and conversion of sheep and beef farms and farmers mainly drove the expansion of dairy farming into the South Island. By 1997, Tasman Agriculture had developed 65 dairying operations in the South Island, with sharemilkers, area managers and farm consultants in charge of establishing production goals and running the business (McLean, 1997).

In Waikato, amalgamations were common in the search for bigger scale (Journeaux, 2002), while in Taranaki and Wairarapa, both acquisitions and conversions took place (Kilsby et al., 1998). Bigger farms introduced another type of problem (Parker, 2002). The trend towards older farm owners coupled with larger farms increased the need for hired staff, moving management away from farm operations. Similarly, it has been reported (MAF, 2001) that recent growth in South Island dairying has occurred largely through "conversions" of sheep, beef and cropping farms.

A long-term view of herd and area dynamics will help to explain the evolution of the industry and the magnitude of the changes that occurred during the nineties (Figure 1.1). During the eighties, total number of herds declined steadily, from 16 thousand herds to 14.4 thousand in 1992. From 1992 onwards, the numbers increased until 1997, before declining again. Total dairy area, on the other hand, stayed constant during the eighties at approximately 940 thousand hectares. However, the area in dairying then increased by 3.8% per annum for the period 1991 to 2005. Cow numbers, meanwhile, grew by 20% from 1981 to 1995 and by 61% from 1991 to 2005, annual growth rates of 1.4% and 4.2% respectively.

It can be seen that years 1991 and 1992 represented an inflection point for the NZ dairy industry (Figure 1.1). During the eighties, the decline in herd numbers coupled with a stagnant total dairy area and the slow increase in cow numbers is synonymous with an industry that was having trouble competing with other land-based industries. Furthermore, there was intense competition within the industry for the available land. Conversely, the nineties saw an industry eager to expand its frontiers. It is worth noting that during the eighties, more than 90% of the dairy herds, dairy cows and total dairy area was located in the North Island.

Figure 1.1 - Evolution of total number of herds, total number of dairy cows and national dairy area (1981-2005)



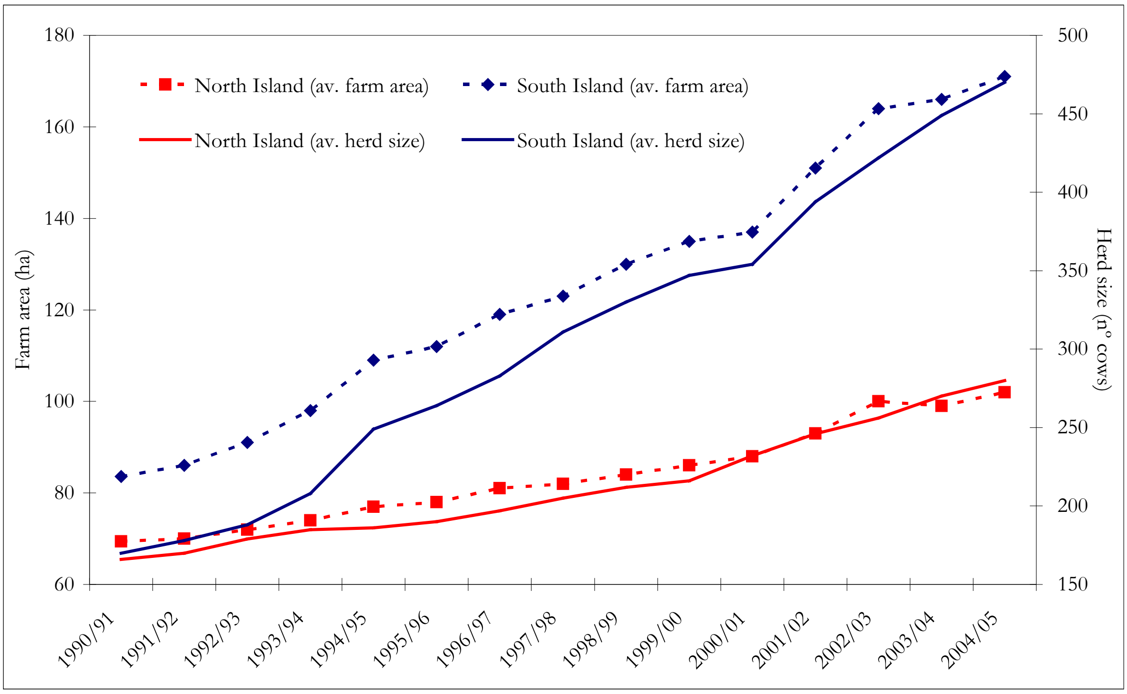
Source: based on Livestock Improvement Corporation

Over the period of 1991 to 2005, herd numbers declined from 14.6 thousand to 12.3 thousand. However, this aggregate figure conceals the extent of the internal transformations. Whereas herd numbers in the North Island declined by 27% from 13.8 thousand in 1991 to 10.0 thousand in 2005, the number of herds in the South Island increased by more than two fold in absolute terms. As a result, 18% of NZ herds are now located in the South Island, compared with only 6% in 1990/91.

NZ's total dairy area has increased by 53% since 1991, reaching 1.4 million hectares in 2004/05. Since 1991, new area added to dairy in the South Island accounted for 63% of the 490 thousand hectares of NZ's new dairy area. Accompanying the geographical expansion in dairy area, cow numbers increased by 1.7 million, to 3.9 million in 2005 from 2.2 million in 1991, of which 728 thousand were in the North Island and 911 thousand were in the South Island.

The long-term trend towards larger units continues. In 2005, an average farm in the South Island had a herd of 470 cows and an area of 171 hectares, compared to 170 cows and 84 hectares in 1991. An average farm in the North Island had a herd of 166 cows and a milking platform of 69 hectares in 1991, whereas in 2005, average herd size was 280 cows and average of area 102 hectares (Figure 1.2).

Figure 1.2 - Average farm size and average herd size by island (1991-2005)

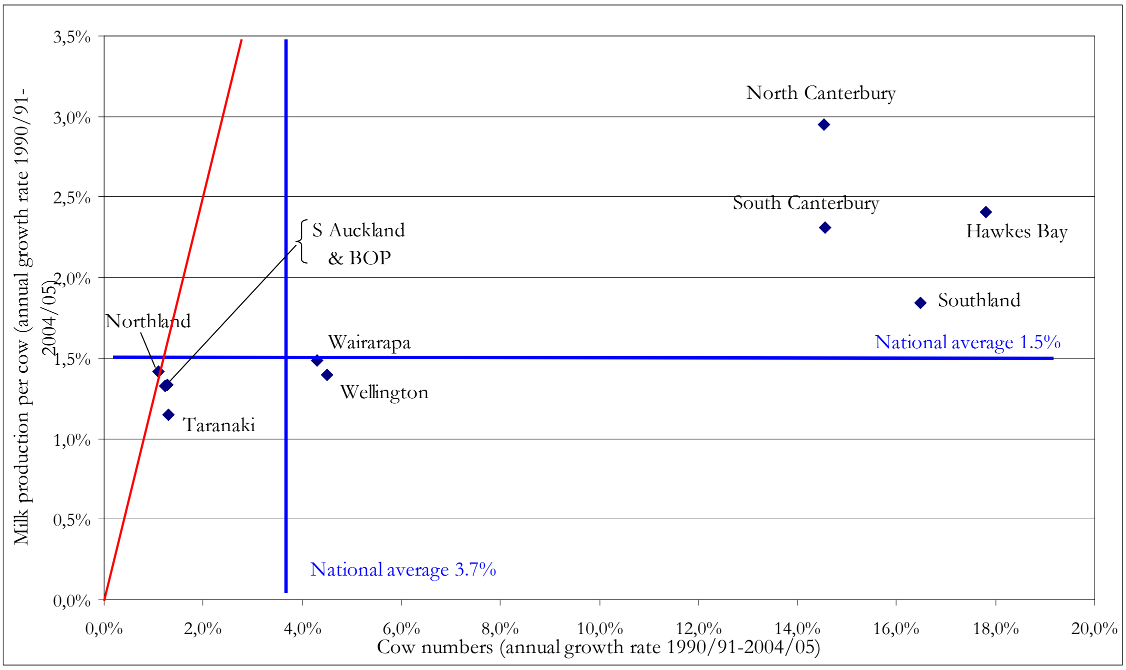


Source: based on Livestock Improvement Corporation

Milk production increases can be achieved through gains in milk production per cow, by increasing the number of cows or both. National average growth rate in cow numbers and milk production per cow was 4% for the period 1990/91 and 1.5% for the period 2004/05 (blue lines in Figure 1.3).

It is clear that, over the period, the drivers of milk production growth have been different among the major regions. Regions in the lower left (South Auckland and Taranaki) grew at lower rates than national average for both variables considered. Conversely, the upper-right quadrant comprises those regions that experienced faster-than-national-average growth rates in both variables. Regions in this quadrant are located in the South Island (North Canterbury, South Canterbury and Southland) and Hawkes Bay, all regions dominated by new dairy farms (Figure 1.3).

Figure 1.3 - Annual growth rate in milk production per cow and cow numbers for the period 1990/91 and 2004/05 (selected regions)



Source: based on Livestock Improvement Corporation

Interestingly, Northland experienced the same growth rates in milk production per cow as in cow numbers (the red line in Figure 2.1, which represents equal growth rates in both variables). All the other regions with different degrees emphasized the growth in cow numbers. This finding agrees with the assertion made by Ruaniyar and Parker (1999) that much of the increase in total milk production in the 1990s appears to have come from increases in the average number of milking cows per farm, partly sustained by increased used of supplementary feeding (number of herds grew more slowly than number of cows for all regions, Table 1.3). Still, it is not clear whether output growth reflects high real productivity or simply more input use.

National milk production grew by 643 million kg milksolids (MS), reaching 1,215 billion kg MS in 2005, up from 572 million kg MS in 1991. The South Island contributed 53% of the increase in output. The outcome of the changes outlined above can be summarised by noting that in 1991, the South Island accounted for 8% of total dairy area, 7% of total number of cows and 7% of national milk output; whereas, by 2005, the South Island accounted for 27% of total dairy area, 27% of total number of cows and 30% of national milk output (Table 1.1).

Table 1.1 - Structural change in New Zealand dairy farming

	Share in milk production		Distribution of cows		Share in total area	
	1991	2005	1991	2005	1991	2005
North Island	93%	70%	93%	73%	92%	73%
South Island	7%	30%	7%	27%	8%	27%

Source: Livestock Improvement Corporation

1.4 Productivity growth as a policy objective

The NZ dairy industry has targeted TFPG at the farm level as a strategic policy objective[2] in order to enhance its sustainable competitive advantage and to improve NZ dairy farmers' profitability (Anderson and Johnson, 2002 and Bodeker and Anderson, 2001). TFP is the most comprehensive measure of productivity as it, ideally, includes all inputs and outputs used in the production process (Coelli et al., 1998 and Diewert and Lawrence, 1999). TFPG is of paramount importance both to sustainability and profitability. A system is economically sustainable if it is capable of attaining "real cost reduction" (Harberger, 1998). Tweeten (1992) claimed that the relative rate of productivity growth has a major influence on the international competitiveness of an industry.

Miller (1984) claimed that productivity change would equal profitability change if there were no effects of prices. Balk (2003) demonstrated that TFPG is the "real" (as opposed to monetary or price-induced) component of profitability change. (Profitability is defined as the ratio of total revenue to total costs.) Similarly, Grifell-Tatjé and Lovell (1999) decomposed profit change (profit defined as firm revenue minus total cost) into a price effect and a quantity effect, which was, in turn, split into a productivity effect and an allocative and scale component. Semantics aside, TFP is a measure of "real" (physical or quantity) performance.

[2] Even though TFP is an adequate measure of performance, it is not widely used and it is often misunderstood. To the best of my knowledge, the NZ dairy industry is the first institution using it as a target measure to guide on-farm improvements

TFP is traditionally calculated as the ratio of total output to the weighted sum of inputs, i.e., the total sum of factors. As a consequence, the TFPG is measured as a ratio of the growth index of outputs to the growth index of inputs. Quite often, growth in TFP is interpreted as a shift of the production function. This interpretation is valid only if the farm is perfectly technically efficient in production, realising the full potential of the given technology. Technically efficient production can be achieved if farmers follow the best practice to apply the technology. To the extent that farmers do not produce with technical efficiency due to differences in their capacity to use new technological knowledge and due to differences in the motivation of farmers, technical progress is not the only source of TFPG. As will be shown later, changes in productivity[3] can be achieved through a better (more efficient) use of the technology applied, through technical innovation (technical progress) or a combination of both (Nishimizu and Page, 1982 and Färe et al., 1994).

Technical efficiency change - the movement towards the "best-practice" frontier, which occurs as a result of either learning-by-doing (leading to the mastery of the technology[4]), adoption of innovations, education or imitation.

Technical progress - the change (shift) in the "best-practice" production frontier (function) as a result of improvements in the design or quality of capital goods or intermediate inputs, discovery of new resources, new methods of doing things, better management and organisational change (e.g., better seeds, new design of milking parlours, cows with better genetic merits and new crop rotations).

Some techniques allow decomposition of changes in productivity into these two parts, i.e., changes in technical efficiency and technical change. Common to such methods is the construction of a production frontier to which each observation is compared. Observations lying on the production frontier are considered to be technically efficient, whereas shifts in the production frontier are interpreted as changes in the technology.

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[3] Definitions of productivity, technical progress and technical efficiency change are presented in Section 4.2.

[4] Technology - the state of knowledge concerning ways of converting resources (inputs) into outputs (Griliches, 1987; Metcalf, 1969).

The decomposition of TFPG into technical progress and changes in efficiency provides more information about the application of production technology. From a policy perspective, this decomposition is important because without using the existing technology to its full potential, it may not be meaningful to embark on the introduction of new technologies. Resources are being wasted if technical efficiency is not attained by the firm (Diewert and Lawrence, 1999). From a management perspective, savings achieved through efficiency are translated into higher income and hence farms have a better chance to survive and prosper (Bravo-Ureta and Rieger, 1991).

Productivity decomposition provides useful information and additional insight into the sources of growth (Brümmer et al., 2002 and Kim and Han, 2001). Given that the sources of productivity growth are, in turn, influenced by different factors, proposing adequate instruments for achieving the goal demands knowledge of the potential explanatory factors (determinants) (Coelli et al., 2003 and Perelman, 1995).

For example, if the industry exhibits a low rate of technical progress, the recommendation should be to encourage investments in new R&D. In doing so, the industry will remove technological constraints that impede the realisation of further productivity gains (Perelman, 1995). On the other hand, if the industry exhibits small gains in technical efficiency, a policy directed to enhance the efficient use of current technology is required to close the gap with the best-practice frontier (Kim and Han, 2001). When a dynamic rate of technological progress coexists with low rates of change in technical efficiency, measures that facilitate adjustment are recommended (Brümmer et al., 2002).

Closing the gap with (or even reaching) the production frontier depends on factors including: the accumulation of human capital either through formal education and training or learning by doing; the level of economic development; (regional) policy framework; an environment conducive to the diffusion of technological knowledge as well as adjustments to external shocks (Nishimizu and Page, 1982 and Tian and Wan, 2000). These activities, in turn, are clearly associated with an active extension policy in some cases and with policy changes in others.

1.5 Productivity estimates for New Zealand dairy farms

Past trends in NZ dairy TFPG failed to achieve the target of 4% selected by the industry (Anderson and Johnson, 2002; Dexcel, 2005 and Johnson and Forbes, 2000). Philpott (1994) estimated annual TFPG for the NZ dairy industry at 0.8% for the period 1973 to 1993. Pringle (2002) mentioned that on-farm productivity gains over the decade 1990 to 2000 were in the range of 1.0% to 1.3%. Over the 1992–2002 decade, TFP for the dairy industry increased on average by 1.4% a year for owner-operated dairy farms and 2.1% a year for sharemilkers (Anderson and Johnson, 2002 and Johnson and Forbes, 2000).

These studies adopted the conventional growth accounting approach and estimated TFPG using the index numbers approach (Törnqvist index and the Fisher Ideal index) (Anderson and Johnson 2002; Johnson and Forbes, 2000 and Philpott, 1994). Growth accounting represents a technique for estimating the contribution of different factors to economic growth. With the aid of marginal productivity theory, growth accounting decomposes the growth of output into growth of labour, land, capital, education, technical knowledge and other miscellaneous sources. In addition, growth accounting approach to TFP measurement is operationalized by finding the difference between growth of output and the growth of the weighted sum of all inputs to obtain output growth associated with technical change or "residual" (Coelli et al., 1998; Diewert and Lawrence, 1999 and Hulten, 2001).

Diewert (1976) has shown that the theory of index numbers is suitable for measuring productivity and various index number formulas are function-specific production. For example, the Törnqvist index can be derived assuming the underlying production function has the translog form and assuming producers are price taking revenue maximisers and price taking cost minimisers. The index number approach to productivity growth has some shortcomings. This methodology assumes that the level of production efficiency is constant and therefore the change in productivity is equivalent to technological change (Coelli et al., 1999). Defined this way, TFPG is at best a measure of Hicks-neutral disembodied technological change and at worst nothing more than "a measure of our ignorance" (Abramovitz, 1956 and Hulten, 2001). More importantly, failure to take account of inefficiency and TEC may produce misleading and biased TFP estimates: while high rates of TP can coexist with deteriorating technical efficiency, relatively low rates of TP can also coexist with improving technical efficiency (Nishimizu and Page, 1982).

Market economies restructure continuously as a response to changing conditions. Two sources of productivity gains drive aggregate efficiency over time. The adoption of new and better technologies and the implementation of more efficient production processes (i.e., technical progress) and the Schumpeterian creative destruction process through which resources are reallocated from less to more productive firms and the entry and exit process. Evidence based on the analysis of panel databases at the micro level suggests that productivity growth at the aggregate level is closely linked to the ability of the economy (or the industry) to efficiently reallocate inputs and outputs across firms (Balk, 2003; Bartelsman and Doms, 2000 and Foster et al., 2001). As will be shown later (Section 2.2), farm dynamics played an important role in the evolution of the NZ dairy industry.

The NZ dairy industry is using TFPG as a target measure to guide on-farm improvements. Balk (2003) and Miller (1984) emphasised that any policy directed at increasing productivity needs to measure and understand the main sources of productivity change as a prerequisite of identifying opportunities for improvement. Aggregate industry-level estimates of TFPG tell us relevant information about the overall state of the industry; however, it impedes stakeholders from extracting applicable on-farm information. If the target is on-farm productivity, it is necessary to provide farmers (and the industry) with individual (farm-level) information with which to benchmark and monitor their progress while retaining aggregate information. Succinctly, can TFP be used to guide policy decisions at an industry level and concurrently be an instrument for strategic management at the farm level?

In this paper, I use a Malmquist index approach to examine interfarm dairy efficiency and productivity. In contrast to other index approaches, the Malmquist approach can distinguish between the two sources of productivity growth: changes in technical efficiency and technical change (Section 1.4). The Malmquist approach identifies the 'best-practice' farms in every period, which gives an efficient production frontier. The best-practice frontier is determined by the observations with the highest productivity. The Malmquist index measures each farm's output relative to that frontier. How much closer an observation gets to the frontier is the efficiency change component; how much the frontier shifts captures the technical change component.

1.6 Geography and technology

Estimates of productivity change at an aggregate industry level are based on some fundamental assumptions, such as the existence of an average "representative farm" and the assumption of optimal behaviour from economic agents, i.e., price taking and profit-maximising behaviour on the part of farmers (Balk, 2003; Coelli et al., 1999 and Grifell-Tatjé and Lovell 1996). Furthermore, it implicitly assumes that all farms face the same technology (Coelli et al., 1999). These assumptions are under challenge as a result of the geographical expansion of dairy farming and the exposition to different agronomic conditions. Since 1992, the spatial distribution of dairy production has changed, greatly adding to the heterogeneity of farming regions and practices. Given the biological nature of agricultural production, the spatial dimension is significant for agricultural technology (Alston, 2002). Soils, climate and landscape differ among regions, influencing, for example, the amount and type of feed grown, the opportunity cost of land and the level of scale economies (Sumner and Wolf, 2002). Additionally, soils, climate and landscape may impose some restriction on the selection and type of technology used. Moreover, the interaction of geophysical factors (location-specific) and the technology adopted may result in different outcomes, encouraging changes in the technology used, creating the basis for a differentiation. In the same way that the environment influences the expression of a genotype, a technology is shaped by the environment in which it is applied.

Interestingly, even though most of the studies reviewed admit that location may influence the technology applied, only the study by Brümmer, Glauben and Thijssen (2002) actually tested whether the technology applied is different among countries. However, presuming the existence of different technologies is customary in inter-country comparisons.

Kumbhakar, Biswas and Bailey (1989) related differences in technology applied to farm size. They found that small, medium and large Utah dairy farmers did not operate under the same technology. Mbaga, Romain, Larue and Lebel (2003) divided the sample of Quebec dairy farmers in two groups (non-maize and maize regions) to assure homogeneity of exogenous conditions. They then estimated the frontier for each sub-sample. However, they did not test whether technologies were different, even though some results pointed in that direction.

Bravo-Ureta and Rieger (1991) attempted to correct their efficiency estimates by introducing location dummies on a sample of dairy farmers from New England (US). Heshmati and Kumbhakar (1994) on Swedish dairy farms, Kumbhakar, Ghosh and McGuckin (1991) on US dairy farms, and Kumbhakar and Heshmati (1995) on Swedish dairy farms, introduced regional and size dummies to accommodate possible differences in productivity among different regions of varying size. Meanwhile, Kumbhakar and Hjalmarsson (1993), on Swedish dairy farms, explicitly accounted for farm-specific characteristics related to location, climate and land quality in an attempt to ensure that inefficiency would not be confounded with farm-specific characteristics. Hallam and Machado (1996), on a sample of Portuguese dairy farms, introduced dummies for location (coastal vs. inland), altitude and handicapped zones to determine whether they influenced technical efficiency. Results were conflicting, as one region that should have appeared to be less efficient turned out to be more efficient. However, as the estimates of technical efficiency obtained were relative to a common frontier, location differences in efficiency may have masked different technologies.

The study by Fraser and Cordina (1999) was performed over dairy farms in Northern Victoria (Australia), assuring homogeneity of exogenous conditions (soils, climate and physical parameters) likely to affect efficiency. Similarly, Piesse, Thirtle and Turk (1996), examining a group of Slovenian dairy farms, mentioned that most of the sample farms had similar alpine terrain, which assured for homogeneity of exogenous conditions. In turn, Haghiri, Nolan and Tran (2004) pointed out that the selection of the regions for the inter-country comparison (US-Canada) was done deliberately, given the similarities in production technology and geophysical conditions among the selected regions.

Jaforullah and Devlin (1996) and Jaforullah and Whiteman (1999), analyzing the technical efficiency of NZ dairy farms, also assumed that the same technology was applied across NZ. This assumption may have been reasonably sound, because in 1992 (the year when the sample was taken), dairy farming was mostly performed in the North Island and particularly in the regions of Waikato and Taranaki (both regions accounted for more than 50% of dairy cows).

Comparing farms against the same frontier is valid if they are on the same production function (i.e., applying the same technology) but using different proportions of inputs

(Piesse, Thirtle and Turk, 1996). Tsionas (2002) reasoned that assuming farms share the same technology when they do not will result in biased measures of efficiency and confusion among technological differences. Battese et al. (2004) emphasised that farms operating under different technologies are not strictly comparable. In fact, given a set of inputs, inefficiency may be confused with the use of a different technology.

1.7 Research objectives

The main goal of this thesis is to study, evaluate and recommend methodologies for dairy farms' productivity growth. This goal is addressed by setting two main objectives:

- to decompose TFP at the farm level
- to evaluate regions' production technologies

The first objective was addressed by estimating TFPG at the farm level. As Balk (2003) and Miller (1984) asserted, any policy directed at increasing productivity needs to measure and understand the main sources of productivity change as a prerequisite of identification of opportunities for improvement. Understanding the sources of productivity growth and gauging its relative contribution would enhance the ability of researchers and extension personnel to identify technological constraints and to target education, training and learning programs to improve technical efficiency. Recommended TFP will be decomposed into its sources, i.e., changes in technical efficiency and technological progress (Chapter 9).

The second objective was addressed by answering the question of whether farms in the two regions considered in this study were operating under the same technology. These two regions were the long-established dairy areas of Waikato-Taranaki and the newly-developed dairy areas of Canterbury-Southland. Empirical evidence suggested that a variety of farming systems have emerged as a result of dairy farming geographical expansion. Therefore, it was important to ascertain whether different regions applied different technologies. Changes in geographic distribution may restrict the benefits of research conducted in one location, as results may not be entirely transferable to the new locations (McCunn and Huffman, 2000). This in turn has important implications to funding new R&D projects because scarce resources will be better exploited in projects that, other things being equal, have interregional spillover effects. To the best of the author's knowledge, this is the first study that tested for differences in technology between regions of the same country. This objective was addressed and achieved in Sections 5.1, 6.1, 7.1 and 8.1.

There is no single study that has attempted to check the robustness of productivity growth and efficiency estimates to input/output variable selection. (See the literature review in Sections 3.2.2 and 3.3.2.) TFP as a comprehensive measure of productivity, theoretically, includes all inputs and outputs in the production process (Coelli et al., 1998 and Diewert and Lawrence, 1999). However, in real life, it is limited by the availability of data. Often aggregation of input and output variables is performed to keep the number of parameters manageable. Bravo-Ureta (1986) cautioned that aggregation of inputs and outputs poses a limitation on production function analysis. The original database and the interest of the researchers in checking the behaviour of some input(s), or the aggregation of them, largely dictate the selection of the input/output set. Strictly, the input/output set chosen is a stylised characterisation of the technology applied.

The present research contributes to knowledge along two lines:

1. As it was demonstrated in the literature review (Sections 3.2.1 and 3.3.1), this is the first study that explicitly assumes and examines differences in technology between regions of the same country.
2. This is the first study that attempts to shed light on the sensitivity of technical efficiency and productivity estimates to the selection of the input/output set, i.e., the characterisation of the technology.

For the empirical analysis, the Malmquist index was used to estimate TFPG. This index, based on distance functions, has become extensively used in the measure and analysis of productivity (Brümmer, Glauben and Thijssen, 2002; Tauer, 1998 and Piesse, Thirtle and Turk, 1996). This index can be decomposed into two additional components, one that measures changes in technical efficiency (i.e., whether farms are getting closer to the production frontier over time) and one that measures changes in technology (i.e., whether the production frontier is moving outwards over time) (Färe et al., 1994). This method is discussed in depth and compared to similar methods in Section 3.3. Stochastic frontier analysis (SFA) was used to gauge the Malmquist productivity index (MPI). The preference of this analysis over the non-parametric Data Envelopment Analysis (DEA) will be discussed in Section 4.3.

This research has a number of limitations. The estimation of TFPG using the MPI requires farm-level (micro) panel data. MAF Policy supplied data. Each year, MAF monitors the production and financial status of farms to create "models." Raw data from the actual farms were used to estimate the MPI. The data were collected for purposes other than the estimation of productivity. Hence, as mentioned above, the measurement of physical output and input data that are required to estimate productivity growth may be subject to some shortcomings discussed in Section 4.6

This study showed how much more information can be obtained from farm-level data and how can it be used to help and guide farmers, researchers and policy makers in achieving the goals of increasing productivity at the farm level (See Sections 8.2–9.4).

CHAPTER 2

2 The evolution of dairy farming in New Zealand with emphasis on key regions

2.1 Introduction

Deregulation of the NZ economy impinged on the relative profitability of agricultural industries, generating the conditions for restructuring within the agricultural sector. Undoubtedly the most important change, given its relevance to the economy, was the transformation of the dairy industry. Even though the number of herds declined slightly, the total size of the industry—as well as total milk output and size of the average farm—increased dramatically. Amid these changes in production, there has been a profound and simultaneous shift in the spatial organisation of dairy production. A brief description of those changes at a national level was presented in the previous chapter (section 1.3).

This chapter has three objectives. First, it will illustrate the magnitude of the changes in some key regions, namely traditional dairy regions (South Auckland and Taranaki) and emerging or non-traditional dairy regions (North Canterbury, South Canterbury and Southland). Given that the spatial dimension is significant for agricultural technology (Alston, 2002), the second objective will be to outline key differences in temperature, rainfall, some aspects of production (i.e., calving dates, dried-off, fertiliser use) and the evolution of productivity per cow and productivity per hectare among key regions. The third objective is to present empirical evidence suggesting that NZ dairy production technology has varied markedly over space and time (Figure 2.5).

2.2 The spatial distribution of dairy farming in New Zealand

Over the period 1991 to 2005, total herd numbers in NZ exhibited a small decline from 13,421 in 1991 to 12,271 in 2005 (Table 2.1). Whereas herd numbers in the North Island declined by 13%, the number of herds in the South Island increased by more than two fold. As a result, 18% of NZ herds are now located in the South Island, compared to only 7% in 1990/91.

Table 2.1 - The number of herds in five subregions and the two Islands of NZ in 1990/91 and 2004/05

	Number of herds		Annual growth rate in number of herds (90/91) – (04/05)	Regional share	
	1990/91	2004/05		1990/91	2004/05
South Auckland	5,141	3,924	-2.0%	38%	32%
Taranaki	2,588	2,006	-1.9%	19%	16%
North Canterbury	122	500	6.6%	1%	4%
South Canterbury	50	154	6.2%	0%	1%
Southland	175	629	8.3%	1%	5%
North Island	12,527	10,010	-1.8%	93%	82%
South Island	894	2,261	4.9%	7%	18%
New Zealand	13,421	12,271	-1.2%		

Source: Livestock Improvement Corporation various years

Herd numbers in the traditional dairy regions of South Auckland and Taranaki, even though they still account for about half of NZ dairy herds, declined by 23%, from 7,729 in 1991 to 5,930 in 2005 (Table 2.1). In contrast, regions like North Canterbury, South Canterbury and Southland showed rates of growth ranging from 6.2% to 8.3%. These regions now account for 10% of NZ dairy herds, whereas in the early nineties, they accounted for only 2% (Table 2.1).

NZ's total dairy area has increased by 53% since 1991, reaching 1.4 million hectares in 2004/05 (Table 2.1). New area has been incorporated into dairy production in all regions. However, the pattern of dairy expansion has been uneven across regions. Since 1991, the new area added to dairy in the non-traditional dairy regions of North Canterbury, South Canterbury and Southland accounted for 43% of the 490 thousand hectares of NZ's new dairy area (Table 2.2).

Table 2.2 - Total dairy area in five subregions and the two Islands of NZ in 1990/91 and 2004/05

	Total dairy area (Thousand ha)		Dairy area as % of total grassland, arable land	
	1990/91	2004/05	1990/91	2004/05
South Auckland	327	370	40%	50%
Taranaki	159	175	36%	46%
North Canterbury	12	99	1%	5%
South Canterbury	5	31	0%	3%
Southland	13	111	1%	10%
North Island	846	1026	14%	20%
South Island	75	386	1%	5%
New Zealand	921	1412	7%	12%

Source: Livestock Improvement Corporation and MAF

The participation of dairy in total grassland and arable land has also increased for all regions. However, during the period 1990/91 to 2004/05, the increments in absolute dairy area coincided with an absolute decline in grassland and arable land area because of forestry developments and, particularly, new investments in property development and lifestyle blocks (MAF, 2001).

Cow numbers increased by 1.64 million, from 2.2 million in 1991 to 3.9 million in 2005 (Table 2.3). The increase in cow numbers occurred across both islands of NZ as shown by the positive rates of growth. However, the rate of growth differs substantially from region to region and between islands. The growth rate in cow numbers for the South Island, at 12.3% per annum, is six times faster than the growth in the North Island, at 2.0% per annum. Consequently, at the end of the period considered, more than one-quarter of NZ dairy cows are in the South Island, compared with only 7% in 1990/91.

At the beginning of the nineties, South Auckland and Taranaki accounted respectively for 40% and 18% of total cow numbers, but have declined significantly to 28% and 13% respectively in 2004/05. Cow numbers in Southland and North Canterbury grew rapidly to account for 16% of total NZ dairy cows in 2004/05, up from 2% in 1990/91 (Table 2.3).

Table 2.3 - Total number of cows in five subregions and the two Islands of NZ in 1990/91 and 2004/05

	Number of cows		Annual growth rate in number of cows (90/91) – (04/05)	Regional share	
	1990/91	2004/05		1990/91	2004/05
South Auckland	901	1,087	1.2%	40%	28%
Taranaki	398	492	1.3%	18%	13%
North Canterbury	27	304	14.5%	1%	8%
South Canterbury	10	98	14.6%	0%	3%
Southland	25	300	16.5%	1%	8%
North Island	2,073	2.804	2.0%	93%	73%
South Island	152	1,063	12.3%	7%	27%
New Zealand	2,225	3,867	3.7%		

Source: Livestock Improvement Corporation

Strong growth in NZ milk production has been recorded in the traditional dairy-producing regions of the North Island. However, the process of expansion and consolidation of dairy production into the South Island, which began in the early nineties, was responsible for much of the increases in milk production over the last decade. National milk production grew at 5.4% per annum, reaching 1,215 million kgs MS in 2005, up from 572 million kgs MS in 1991 (Table 2.4).

Despite a positive growth rate of 3.3% per year, the North Island's contribution to total milk production has been declining steadily since the beginning of the period, falling from 93% to 70% (Table 2.4). South Auckland and Taranaki increased their production at a rate below the North Island average. At the beginning of the period, the share of both regions in total milk output amounted to 59%. By 2005, their combined contribution decreased to 40% of national milk output (Table 2.4).

In contrast, South Island milk output has been growing at an annual rate of 14.5%, contributing to 30% of NZ's milk output in 2005. North Canterbury and Southland have been robustly expanding their milk production at 17% and 18% a year respectively. As a result, they are rapidly approaching Taranaki's share in milk production (Table 2.4).

Table 2.4 - Milk production, annual growth rate and regional share in five subregions and the two Islands of NZ in 1990/91 and 2004/05

	Milk production ('000 ton. milksolids)		Annual growth rate in milk production (90/91) – (04/05)	Regional share	
	1990/91	2004/05		1990/91	2004/05
South Auckland	237	336.1	2.5%	41%	28%
Taranaki	105	149.2	2.4%	18%	12%
North Canterbury	7	111.7	17.5%	1%	9%
South Canterbury	3	35.2	16.9%	0%	3%
Southland	8	107.3	18.4%	1%	9%
North Island	531	846	3.3%	93%	70%
South Island	41	369	14.5%	7%	30%
New Zealand	572	1,215	5.4%		

Source: Livestock Improvement Corporation

The long-term trend towards larger units continues. Journeaux (2002) mentioned that over the period 1990 to 2001, average farm size in Waikato increased from 65 hectares and 171 cows to 85 hectares and 240 cows. For Canterbury, farm averages icreased from 96 hectares and 202 cows to 158 hectares and 451 cows over the same period. For all regions considered, both average herd size and average farm area have increased, albeit faster for herd size (Table 2.5 and Table 2.6). However, farm size increases have not been homogeneous across regions. Once again, growth rates for non-traditional dairy regions exceeded those of traditional dairy regions (Table 2.5 and Table 2.6).

Table 2.5 - Average herd size and annual growth rate in five subregions and the two Islands of NZ in 1990/91 and 2004/05

	Average herd size		Annual growth rate 1990/91 – 2004/05
	1990/91	2004/05	
South Auckland	175	277	3.3%
Taranaki	154	246	3.2%
North Canterbury	224	609	8.0%
South Canterbury	194	636	8.4%
Southland	145	477	8.1%
North Island	166	280	3.7%
South Island	170	470	7.4%
New Zealand	166	315	4.6%

Source: Livestock Improvement Corporation

Table 2.6 - Average farm area and annual growth rate in five subregions and the two Islands of NZ in 1990/91 and 2004/05

	Average farm area		Annual growth rate 1990/91 – 2004/05
	1990/91	2004/05	
South Auckland	64	94	2.9%
Taranaki	61	87	2.9%
North Canterbury	99	198	5.7%
South Canterbury	91	203	6.2%
Southland	76	177	5.5%
North Island	69	102	2.8%
South Island	84	171	5.2%
New Zealand	70	115	3.6%

Source: Livestock Improvement Corporation

South Auckland and Taranaki experienced a net loss in number of herds that totalled 1,799 herds. Conversely, the three South Island regions showed evidence of a net gain in herd numbers of 936 herds (Table 2.1). Over the period, total dairy area increased by 59 thousand hectares for South Auckland and Taranaki and by 221 thousand hectares for the three South Island regions (Table 2.2). Furthermore, South Auckland and Taranaki experienced slower rates of growth in average herd size and average farm area than the three South Island regions (Table 2.5). Therefore, it seems that the predominant phenomenon for South Auckland and Taranaki was the exit of farms and the subsequent redistribution of cows and land among existing farms. Conversely, the three South Island regions showed the influence of new entrants, new farms and new herds that were larger than the average herd.

2.3 Main differences between traditional and non-traditional dairy regions

Milk production in NZ is still predominantly based on grazing. However, by 1998 most farms used some kind of "imported feeding," either in the form of grazing-off or purchased feeds, whereas traditionally all farms had been self-contained for feed (Holmes, 1998). Furthermore, some excess of enthusiasm even induced the use expensive supplementary feeding, such as grains and bypass protein (Holmes, 2003).

Pasture production varies substantially among dairy regions, causing regional differences in productivity per unit of area (Holmes, 2003). Different agronomic conditions imply the use of different types and rates of fertiliser to maintain or increase pasture production. Wells (2001) reported statistically significant differences in fertiliser applications across NZ regions (Table 2.7).

Table 2.7 - Milk production per hectare and fertiliser application in four subregions of NZ

	Milk production (kg MS)		Fertilizer application (kg/ha)	
	Per hectare	Per cow	Nitrogen	Potassium
Waikato	804	288 †	69	63
Taranaki	1024 ‡	314	90	60
Canterbury	981 ‡	366 ‡	169 ‡	32 †
Southland	927	388 ‡	65	82 ‡

‡ significantly greater than the overall average

† significantly less than the overall average

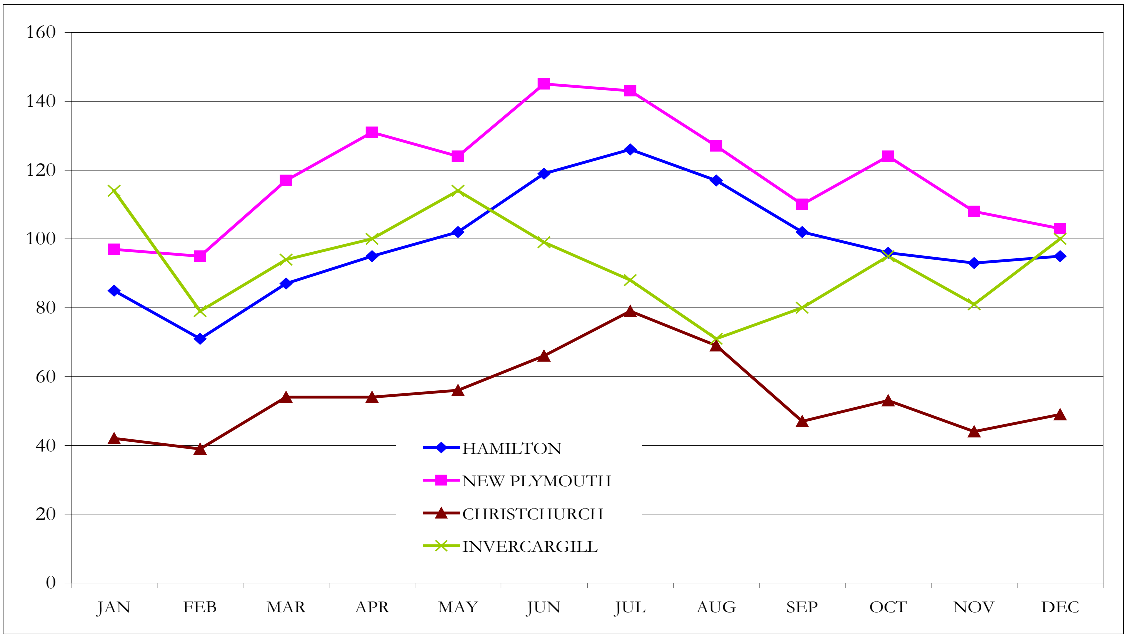
Source: Wells (2001), page 55.

Pasture growth in Northland exhibits two low growth periods in winter and summer, creating problems to balance feed demand and supply (Robinson, 1999). Farmers have responded by implementing summer crops or by applying split calving (spring and autumn calving) to smooth feed demand. Summer crops are common in all of the North Island, and split calving adoption has increased over time, whereas winter crops are more common in the South Island (Robinson, 1999).

Robinson (1999) emphasised the differences between Northland and other dairy regions when comparing winter pasture growth rates with the spring peak growth. In Northland, winter growth rates are half of the rate of the spring peak, at Ruakura, 27% and in Southland, 10%. On the other hand, Gaul and Hughes (1996) explained that pasture growth on the east coast of the South Island (Canterbury, North Otago) is more closely matched with the seasonal pattern of production of NZ dairy farmers. They pointed out that alternative feed resources are widely available, conferring a distinct characteristic to the Canterbury dairy systems. Additionally, irrigation has been applied throughout some regions, increasing the gap in pasture production among regions. Finally, they asserted that irrigation made dairy farming viable in Canterbury.

Pasture production and pasture growth are determined by temperature and rainfall, among other things (Hodgson, 1999). Both characteristics display great variation among regions. In Canterbury, rainfall ranges from an average of 500 mm on the coast to 1,000 mm in the foothills. Generally, rainfall is evenly spread throughout the year (Gaul and Hughes, 1996) (Figure 2.3). Alternatively, research stations in Northland, Ruakura and Taranaki experience annual rainfalls of 1,324 mm, 1,330 mm and 1,182 mm respectively. Moreover, rainfall distribution over the year is relatively more even in Ruakura and Taranaki than in Northland, which is well-known for its wet winters and dry summers (Hodgson, 1999) (Figure 2.1).

Figure 2.1 - Average monthly rain at four climate stations in New Zealand (mm)

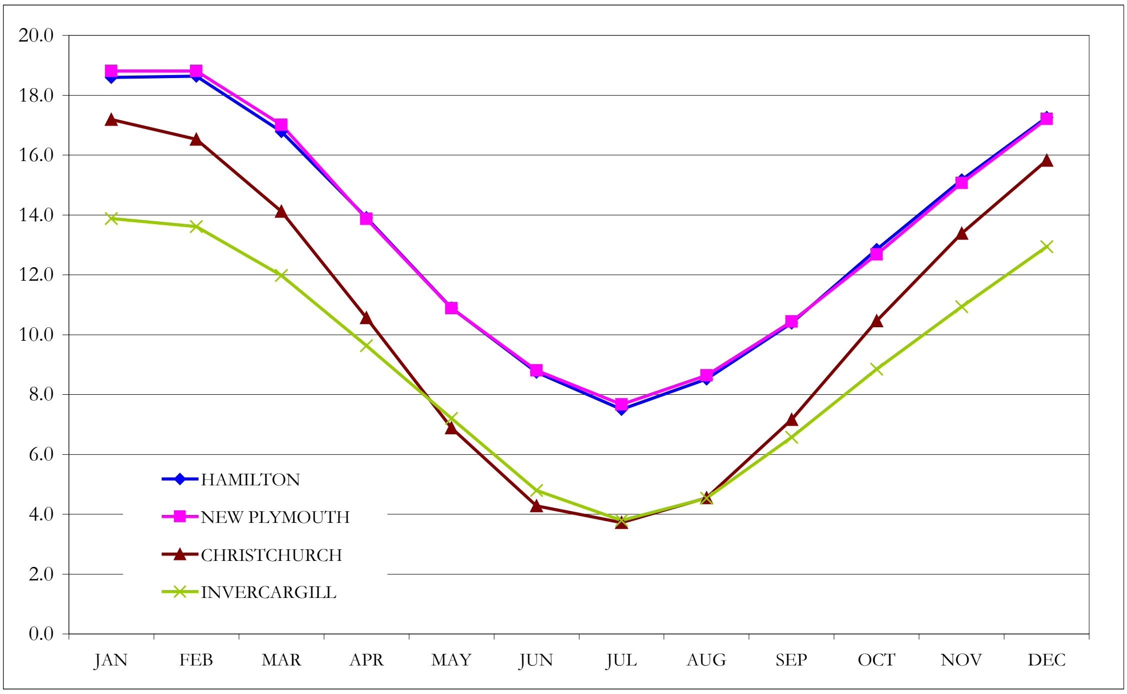


Source: NIWA

Average soil temperature in Northland are above 10ºC and consistently higher than those recorded in Taranaki and Ruakura. Canterbury experiences up to 90 frosts in winter (Gaul and Hughes, 1996), while Northland has a few light frosts (Hodgson, 1999) (Figure 2.2).

Calving dates also differ among the regions, with a north to south gradient observable (Holmes, 2003). The median calving date for Northland was August 5th and for the South Island, September 2nd. Also, average days in milk are reported to be longer in the South Island than in the North Island. Irrigation (in the South Island) ensures a good supply of pasture in summer, making it unnecessary to dry-off cows early (Gaul and Hughes, 1996).

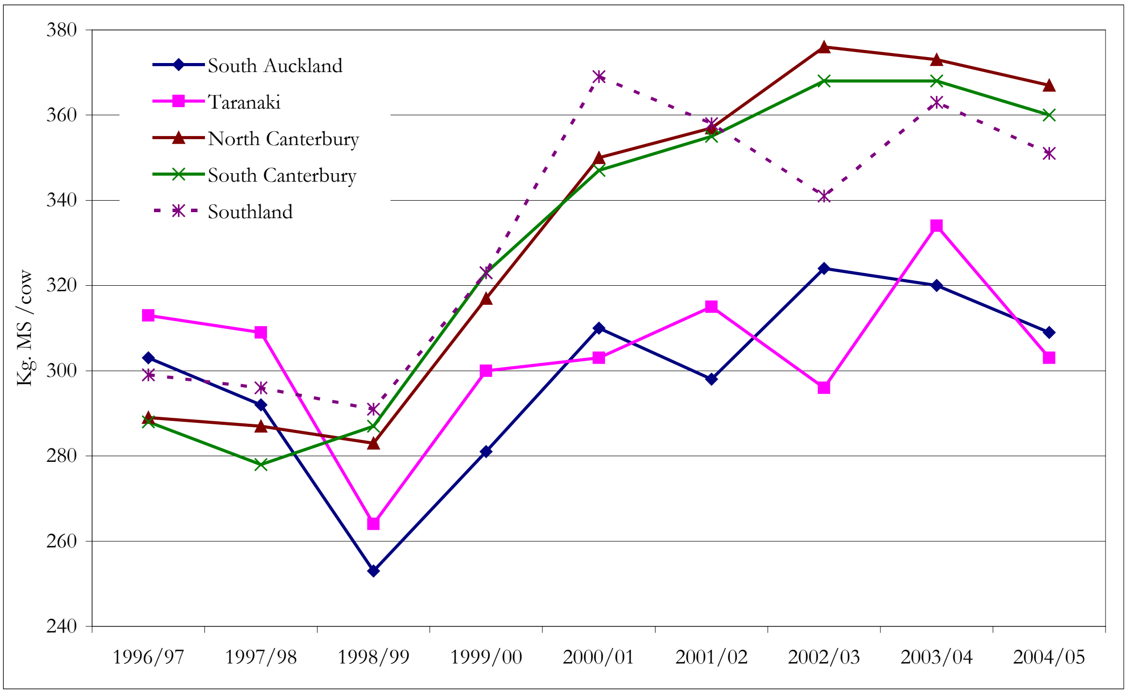
Figure 2.2 - Average soil temperature at four climate stations in New Zealand (ºC, at 10 cm height)



Source: NIWA

Over the period 1996/97 to 2004/05, differences in average regional productivity per cow increased significantly among regions. At the beginning of the period, productivity per cow ranged between 288 kg MS/cow for North and South Canterbury and 314 kg MS per cow for Taranaki. By the end of the period, average productivity was 367 kg MS/cow for North Canterbury and 303 kg MS/cow for Taranaki. Moreover, productivity per cow in both regions of the North Island showed a similar pattern of evolution, as did the three regions of the South Island. Over the period, growth rate in productivity per cow was 1.5% per annum for South Auckland and 0.7% per annum for Taranaki. Meanwhile, productivity per cow grew at an annual rate of 4% for Canterbury and 2.8% Southland (Figure 2.3).

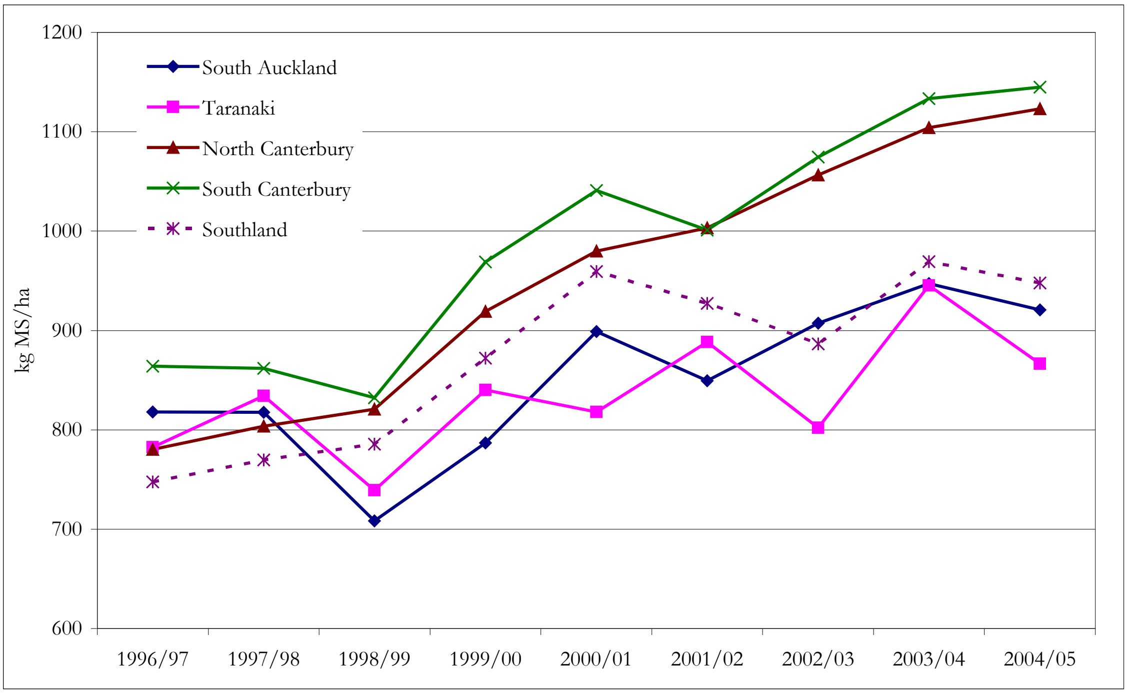
Figure 2.3 - Evolution of the productivity per cow in five subregions of NZ over the period 1996/97 and 2004/05



Source: Livestock Improvement Corporation

Differences in productivity per hectare among regions increased over the period, albeit less significantly. At the beginning of the period, productivity per hectare ranged between 747 kg MS/hectare for Southland and 864 kg MS/hectare for South Canterbury. By the end of the period, average productivity was at 1,145 kg MS/hectare for South Canterbury and at 867 kg MS/hectare for Taranaki. Furthermore, productivity per hectare evolved similarly for North Canterbury and South Canterbury, showing strong growth and for South Auckland and Taranaki, presenting moderate growth. For Southland, the evolution of productivity per hectare showed a strong growth over the first half of the period (up to season 2000/01) and then a halt over the second period (Figure 2.4). Finally, over the period, growth rate in productivity per hectare was 2.5% per annum for South Auckland and 1.7% per annum for Taranaki, but 4.6% for Canterbury and 3.2% Southland (Figure 2.4).

Figure 2.4 - Evolution of the productivity per area in five subregions of NZ over the period 1996/97 and 2004/05



Source: Livestock Improvement Corporation

Differences in dairying between the South Island and the North Island are well explained by northern dairy farmers who migrate south (Garret, 1993; Lee, 1993 and Topham, 1993). Gaul and Hughes (1996); Hodgson (1999); O'Flaherty (2000); Riddick (1991) and Robinson (1999) provide comprehensive information about regional differences in rainfall, temperature and soils across NZ. Wells et al. (1998) found significant differences in dairy farming input use across different regions of NZ. Finally, industry statistics (Livestock Improvement Corporation) showed a consistent divergence in productivity per cow and productivity per hectare among the subregions.

2.4 Technological trajectories for selected regions in New Zealand

As shown above, productivity per cow and productivity per hectare differed over time between traditional and non-traditional dairy regions. With input coefficients of the same dimension, a production technique may be represented by a point in a two-dimensional technology space (Farrell, 1957). Given that technical change is defined as an alteration in the value of the input coefficients, it will appear in the technology space as a movement in the location of the representative point.

The inputs selected were "cows" and "labour." Cow numbers were taken from the Livestock Improvement Corporation Annual Report. Statistics New Zealand provided labour statistics for the census years 1991, 1996 and 2001. First, partial factor productivity measures were estimated for each region and input, i.e., kg milksolids produced either per cow or per worker. Next, following Farrell (1957), the reciprocal of the partial factor productivity measures was taken and multiplied by one thousand, transforming all measures into the quantity of cows needed to produce one tonne of milksolids and, similarly, the number of workers needed to obtain one tonne of milksolids. The estimation was performed for all regions and financial years 1990/91, 1995/96 and 2000/01[5].

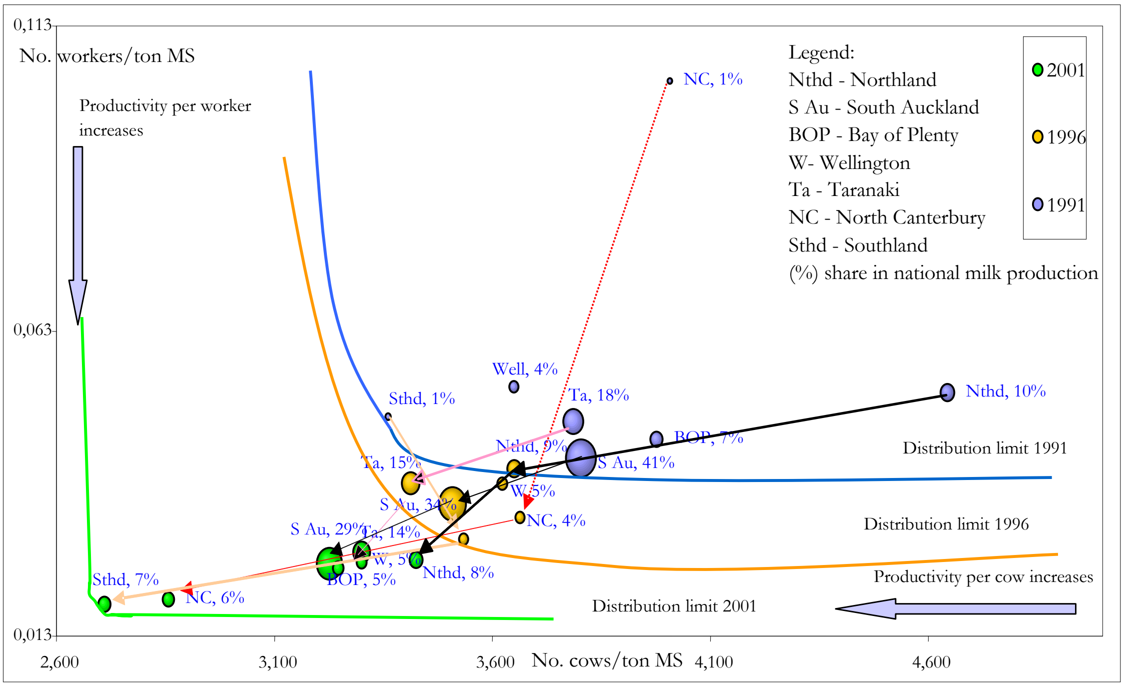
The evolution of the production technology (for some regions to avoid cluttering) is portrayed below (Figure 2.5). Migration to the lower-left quadrant indicates improvements in both partial productivities. On the other hand, migration to the lower-right quadrant shows a decrease in productivity per cow. All regions showed improvements in both measures of productivity, except Southland between 1991 and 1996, which exhibited a decline in productivity per cow.

In 1991, the limit of the distribution (the unit isoquant given the transformation of the data) of regional technologies was marked by Southland and South Auckland, while North Canterbury and Northland were far away from it. Also, the dispersion of the regions in the technology space is greater than in the other two years. The dispersion declined for 1996 as a result of the catch-up of Northland and North Canterbury on the other regions, coupled with the slow move of the regions that delimited the frontier (Southland and Taranaki). Technological dispersion increased in 2001 as a consequence of the relatively strong growth in productivity of Southland and North Canterbury vis-à-vis those experienced by other regions. Projecting the distance between any pair of points (of the same region) on to the horizontal axis allows comparing the improvement in productivity per cow among regions. It can be seen that between 1996 and 2001, productivity per cow increased relatively more for Canterbury and Southland than for South Auckland and Taranaki.

[5] Years selected were determined by labour data availability. Census data from Statistics New Zealand were available for years 1991, 1996 and 2001.

It can be seen that both newly-developed dairy areas (Southland and North Canterbury) and the three traditional dairy regions (Taranaki, South Auckland and Bay of Plenty) conformed two separate clusters. Moreover, Northland and Wellington are more similar, from the technological standpoint, to the traditional dairy regions.

Figure 2.5 - Regional technological trajectories for selected regions in NZ among 1991, 1996 and 2001



Source: based on Livestock Improvement Corporation and Statistics New Zealand

2.5 Conclusion

The geographical expansion of dairy farming has brought challenges to understanding the representative NZ dairy-farming system. Traditional dairy regions in the North Island experienced a net reduction in herd numbers, but small gains in new area devoted to dairy. Conversely, emerging or non-traditional dairy regions experienced increases in new area devoted to dairy and the entrance of new, large herds. These, in turn, have encouraged an increasing divergence in farm and herd sizes across regions. Some authors (Jaforullah and Devlin, 1996; Jaforullah and Whiteman, 1999; Journeaux, 2002 and Kilsby et al., 1998) gave evidence of farm dynamics, the different processes leading to scale increases and the differences in both the organisational arrangements, as well as farmers' backgrounds.

Others gave evidence of the differences in dairying between the South Island and the North Island (Garret, 1993; Lee, 1993 and Topham, 1993). There is comprehensive information about regional differences in rainfall, temperature and soils (Gaul and Hughes, 1996; Hodgson, 1999; O'Flaherty, 2000; Riddick, 1991 and Robinson, 1999), as well as input use (Wells, 2000) across different regions of NZ. Furthermore, the growth rate in productivity per cow and productivity per hectare diverged between traditional and non-traditional, favouring the latter. Finally, empirical evidence suggests the existence of different technological trajectories between traditional and non-traditional dairy regions.

All these factors may have contributed to departures from the traditional paradigm of a common NZ farming system. Therefore, it may be argued that a variety of farming systems have emerged over time, increasing the heterogeneity of dairy farming across NZ.

CHAPTER 3

3 A review of previous studies on dairy farm efficiency and productivity

3.1 Introduction

Empirical analysis of efficiency and productivity using frontier production functions is common in agriculture. Battese (1992) presented an excellent survey about frontier production functions and its empirical applications on agricultural economics. Coelli (1995), in turn, discussed the two primary methods for frontier estimation (econometric and mathematical programming) and provided a selected list of applications into agriculture, along with industries analysed and the methodology employed.

The purpose of this review is to discuss those studies that focus on dairy farm efficiency and productivity. Only publications in major economic journals have been reviewed. Hence, the list is comprehensive but far from exhaustive. In order to allow a better discussion, the studies reviewed were classified depending on the objective of their analysis. Efficiency studies will be reviewed first, followed by those that aimed to estimate and decompose TFPG.

Most studies focus their attention on the functional forms (Bravo-Ureta and Rieger, 1990; Dawson, 1986 and Mbaga, Romain, Larue and Lebel, 2003); alternative assumptions regarding the distribution of inefficiency (Battese and Coelli, 1988; Jaforullah and Devlin, 1996 and Mbaga, Romain, Larue and Lebel, 2003); the characteristics of the inefficiency with respect to temporal variation (Cuesta 2000 and Heshmati and Kumbhakar, 1994) or its decomposition into a persistent and residual component (Kumbhakar and Heshmati, 1995) and estimation methods (Hallam and Machado, 1996). Finally, Mbaga, Romain, Larue and Lebel (2003) compared the efficiency estimates obtained by both methodologies, parametric and non-parametric frontiers.

This review will be made along three lines not explored before: the underlying assumption about technology; the input/output variables introduced in the production function and the exogenous variables used as determinants of technical inefficiency among farms.

3.2 Previous studies in dairy farm efficiency

There have been a large number of studies of farm efficiency levels on dairy farms (Table 3.1). Twenty-four articles were reviewed from 1985 up to 2004.

According to the measurement approach, they can be divided into parametric or non-parametric models. Fifteen studies applied parametric models (Table 3.3), seven studies applied non-parametric techniques (Table 3.4) and two studies applied both approaches (Table 3.5). Meanwhile, Haghiri, Nolan and Tran (2004) (Table 6) developed a new econometric methodology to estimate non-parametric stochastic frontier using the theory of General Additive Models (GAMs). The frontier was estimated through a backfitting algorithm.

Given the focus of the present literature review and that the methods and measurement approaches employed to identify the frontier have been extensively reviewed before, only a brief outline will be presented here. (Readers are referred to Ali and Seiford, 1993; Førsund and Sarafoglou, 2002 and Seiford and Thrall, 1990 for DEA and to Bauer, 1990; Kumbhakar, 2000 and Green, 1993 and 1997 for econometric modelling for full reviews and discussions.)

Those studies that applied econometric models to obtain efficiency estimates can be further divided into deterministic and stochastic. The difference between them relies on the treatment of the error term. The stochastic frontier models, unlike deterministic, decomposed the error term into two components: standard noise, and a one-sided non-negative term reflecting departures from the frontier, i.e., inefficiency. Stochastic frontiers were applied in fourteen cases and deterministic frontiers in three. The most frequent method for the estimation of the parameters of the stochastic frontiers is Maximum Likelihood (ML).

Table 3.1 - Summary of dairy efficiency studies

Author(s)	Geographic scope (*)	Methodology	Database
Ahmad and Bravo-Ureta (1996)	State	Econometric	Panel
Asmild et al. (2003)	National	DEA	Cross section
Battese and Coelli (1988)	Regional	Econometric	Panel
Bravo-Ureta (1986)	Regional	Econometric	Cross section
Bravo-Ureta and Rieger (1990)	Regional	Econometric	Panel
Bravo-Ureta and Rieger (1991)	Regional	Econometric	Cross section
Cloutier and Rowley (1993)	Province	DEA	Cross section
Cuesta (2000)	Province	Econometric	Panel
Dawson (1985)	Regional	Econometric	Panel
Dawson and White (1990)	International	Econometric	Panel
Fraser and Cordina (1999)	District	DEA	Cross section
Haghiri, Nolan and Tran (2004)	States (in 2 countries)	non-parametric Stochastic	Panel
Hallam and Machado (1996)	Regional	Econometric	Panel
Heshmati and Kumbhakar (1994)	National	Econometric	Panel
Jaforullah and Devlin (1996)	National	Econometric	Cross section
Jaforullah and Whiteman (1999)	National	DEA	Cross section
Kumbhakar, Biswas and Bailey (1989)	State	Econometric	Cross section
Kumbhakar, Ghosh and McGuckin (1991)	National	Econometric	Cross section
Kumbhakar and Heshmati (1995)	National	Econometric	Panel
Kumbhakar and Hjalmarsson (1993)	National	Econometric	Panel
Mathijs and Vranken (2001)	National	DEA	Cross section
Mbaga, Romain, Larue and Lebel (2003)	Province	Econometric/DEA	Cross section
Piesse, Thirtle and Turk (1996)	National	Econometric/DEA	Panel
Weersink, Turvey and Godah (1990)	Province	DEA	Cross section

(*) geographic dispersion of farms: district < state = province < regional < national

Three studies, out of fourteen that applied stochastic frontiers, used traditional panel data models to gauge (in)efficiency (Ahmad and Bravo-Ureta, 1996; Hallam and Machado, 1996 and Piesse, Thirtle and Turk, 1996). The advantage of these methods in the estimation of the inefficiency effects is the relaxation of two assumptions of the stochastic frontier methodology. First, in traditional panel data methods, there is no need to specify a particular distribution for the inefficiency effects. Second, there is no need to assume that technical efficiency and variables (inputs) included in the model are uncorrelated. The first assumption implies that management does not affect the productivity of inputs. The drawback of traditional panel data methods vis-à-vis ML is that efficient and inefficient firms both have the same influence in the shape of the frontier (Coelli, Rao and Battese, 1998; Greene, 1997 and Hallam and Machado, 1996).

Stochastic frontier models by Heshmati and Kumbhakar (1994), Kumbhakar and Heshmati (1995) and Kumbhakar and Hjalmarsson (1993) mixed traditional panel data methods with ML methods. Kumbhakar and Hjalmarsson (1993) developed a method, using within transformation and the Expectation-Maximisation (EM) algorithm, to separate technical inefficiency from farm-specific characteristics like location, climate and land quality. Technical inefficiency is assumed to be identically and independently distributed over time and across farms. Heshmati and Kumbhakar (1994) presented a modified version (instead of the EM algorithm they applied ML) and decomposed the error term into a farm-specific component (assumed to be time invariant), technical inefficiency (allowed to vary over time and across farms) and a white noise term. Finally, Kumbhakar and Heshmati (1995), in a multi-step procedure, decomposed technical inefficiency into a persistent farm-specific component (time invariant) and a farm- and time-specific residual component. They applied random effects and ML. All three models are computationally cumbersome.

The non-parametric approach (DEA) was applied in seven cases. DEA can be output- or input-orientated. In the first case, inefficiency arises because output can be increased without augmenting input quantities. Conversely, input-orientated DEA measures inefficiency as the amount by which input quantities can be proportionally reduced while still maintaining output quantity. DEA measures (input- or output-orientated) of technical inefficiency can be obtained under the assumption of constant returns to scale (CRS) or variable returns to scale (VRS). CRS assumption is valid if all farms operate at optimal scale. VRS allows the assumption about optimal scale to be relaxed and permits the calculation of technical efficiency free from scale efficiency.

In regard to the above typology, all the studies applied input-orientated analysis, with the exception of Fraser and Cordina (1999), who applied both orientations. The choice of orientation has minor influences on efficiency scores (Coelli, Rao and Battese, 1998). However, it may be argued that farmers are more willing to increase output given input quantities (output-orientated measure) than the reverse, i.e., given the output, reduce input use. Furthermore, given that some resources are fixed (in the short run), it is more appropriate to produce as much output as possible.

3.2.1 The underlying assumption about technology

According to the frontier approach, it is assumed that all farms are confronted with a single production frontier and therefore share the same underlying technology. Differences among farms arise in the efficiency with which technology is used. Assuming farms share the same technology when they do not will result in biased measures of efficiency and confusion among technological differences.

Few studies on efficiency addressed the issue of technological differences among farms. One early example is Kumbhakar, Biswas and Bailey (1989). They divided the sample of Utah dairy farmers into three groups according to total value of sales. They then estimated the frontier of each group and the pooled frontier (all groups together). The likelihood-ratio test (LR test) was used to test the null hypothesis that all farms operated under the same technology. They accepted the alternative hypothesis that production structure differs across farms of different sizes (p 601, footnote 4). Similarly, Hallam and Machado (1996) tested whether specialised[6] and non-specialised Portuguese dairy farms operated under the same technology. Hypothesis testing was performed by a Chow test for equality of parameters of frontiers estimated for both farm types. They accepted the null hypothesis that both sub-samples are confronted with the same production frontier.

[6] Specialised and non-specialised referred to the share of dairy income in total farm income.

Mbaga, Romain, Larue and Lebel (2003) divided the sample of Quebec dairy farmers into two groups (non-maize and maize regions) to assure homogeneity of exogenous conditions. They then estimated the frontier for each subsample. However, they did not test whether technologies were different even when some results pointed in that direction.

In practice, farms may adopt different technologies for a variety of reasons. Soils, climate and landscape differ across regions, influencing for example, the amount and type of feed grown, the opportunity cost of land and the level of scale economies (Sumner and Wolf, 2002). In turn, these exogenous conditions may impose some restriction in the selection and type of technology used. Thurow and Holt (1997) stressed the importance of heritage and past investments in determining the type of technology that is most successful, as well as the management preferences of individual farmers.

The evolutionary theory claims that technologies evolve along specific pathways or trajectories (Brennan and Wegener, 2003). Innovation is usually a continuous incremental process within a technological regime. Rather infrequently, innovation is radical, i.e., abandonment of a particular technological regime.

Arthur (1989) asserted that a dominant technology could be progressively "locked-in," seriously restricting the movements from one state to the next and confining innovation to a narrow corridor of developments. Adoption of a new capital good may require changes in existing equipment, bringing in additional cost of adjustment. In addition, existing management and labour skills may limit or even prevent innovations. This "interrelatedness" limits the scope of adoption (Brennan and Wegener, 2003).

Other factors, like uncertainty about the performance of new, unproven technology, coupled with the irreversibility of some investments in fixed assets may restrict adoption decisions (Purvis, Boggess, Moss and Holt, 1995). Related to irreversibility, there is also the issue of the non-transferability to other uses (e.g., a milking machine can only be used for dairying).

Therefore, at the regional level, innovation is incremental and strongly shaped by existing socioeconomic structures and the behaviour of their agents. Radical innovations, in turn, tend to appear in new areas and are less predetermined and dominated by successful structures (Tödtling, 1992). Similarly, at any point in time, new firms entering the industry are confronted with different technologies. The choice of a particular technological regime is largely random and only through ex-post competition, can uncertainty about competing design be resolved (Arthur, 1989). Following the logic of the evolutionary theory, some educated guesses can be made about the outcomes of the choices the new firms face. New firms entering the industry in a well-established region will be prone to adopt the dominant paradigm. On the other hand, if the new entrant chooses a new location where a priori there is no dominant technological paradigm, it will be less conditioned and more able to adopt a different technology (Tödtling, 1992).

The above-mentioned is particularly true in agricultural production, where the interaction of geophysical factors (location-specific) and the adopted technology may result in different outcomes. As Alston (2002) asserted, the biological nature of agricultural production implies that the spatial dimension is significant for agricultural technology. In fact, a successful technology applied in one location may not be entirely transferable to a new location.

Given the spatial dimension of agricultural technologies, it is important when measuring efficiency to correctly identify the technology applied. Otherwise, inefficiency will be confused with using an inferior technology (Battese el al., 2004). Fraser and Cordina (1999) stressed the importance of assuring homogeneity of exogenous conditions (soils, climate and physical parameters) likely to affect efficiency. They asserted that such technical efficiency differences are the results of managerial ability. Presumably, they were stressing the importance of ensuring that all farms operate under the same technology in order to gauge the correct efficiency estimates.

In view of the above-mentioned, it would be more accurate to say that assuring homogeneity of exogenous conditions (soils, climate and physical parameters) is crucial insofar as technology applied is likely to be the same (albeit with different rates of adoption) and hence true estimates of (in)efficiency may be obtained. Technical efficiency differences from a group of farms that share homogeneous exogenous conditions and operate under the same technology are, therefore, the result of managerial ability.

The geographical spread of the datasets of the papers reviewed is mixed. Only one study has a district scope (Fraser and Cordina, 1999). Six of them are based on provincial or state data and another six on regional data. The rest are classified as follows: one deals with farms in the province of Ontario, Canada and the state of New York, United States (Haghiri, Nolan and Tran, 2004), one pooled data from two countries (Dawson and White, 1990), while nine have national/country coverage.

Bravo-Ureta and Rieger (1991) attempted to correct their efficiency estimates by introducing location dummies to capture effects on the placement of the production technology. However, the coefficient of the slope parameters in the production function were the same for all farms, i.e., all farms face the same frontier.

Haghiri, Nolan and Tran (2004) pointed out that the selection of the province and state for the inter-country comparison was done on purpose, given the similarities in production technology and geophysical conditions between them. Even though the non-parametric stochastic frontier was estimated for both samples independently, no formal test was conducted to check whether technology applied was the same.

Regarding the studies at a country level, Piesse, Thirtle and Turk (1996) mentioned that most of the sample farms have similar alpine terrain, which assures homogeneity of exogenous conditions. Heshmati and Kumbhakar (1994), Kumbhakar, Ghosh and McGuckin (1991) and Kumbhakar and Heshmati (1995) introduced regional and size dummies to accommodate possible differences in productivity among different regions and size, but all farms face the same frontier. Kumbhakar and Hjalmarsson (1993) explicitly account for farm-specific characteristics related to location, climate and land quality, given that inefficiency should not be confounded with farm-specific characteristics.

For the NZ studies (Jaforullah and Devlin, 1996 and Jaforullah and Whiteman, 1999), the authors assumed that all farms face the same frontier and hence, all farms applied the same technology.

3.2.2 The input/output variables used

The availability and reliability of data largely dictate the selection of variables to estimate the frontier. Some authors reported inconsistencies in the measurement of the same variable across the dataset. Others found that relevant variables were not surveyed or that the aggregation precludes the extraction of accurate information. In some cases, variable selection is done deliberately to allow testing some hypotheses of interest. Aggregation of variables under different headings, such as capital, animal expenses, crop expenses and miscellaneous expenses, is common. However, none of the aggregates are comparable across studies. In summary, one can find as many input/output arrangements as studies performed. (Tables 3.3, 3.4, 3.5 and 3.6 list the variables included in each study.)

An interesting finding of this review was that no single study attempted to check the robustness of efficiency estimates to selection of input/output variables. As Bravo-Ureta (1986) cautioned, aggregation of inputs and outputs poses a limitation on production function analysis.

Bearing this in mind, the most common variables (input and output) included in the estimation of frontiers will be discussed below. Along the lines of this review, variables used for the estimation of parametric frontiers will be addressed first, followed by those used in DEA.

Parametric estimation is restricted to a single output measure. In ten cases, output was measured using total milk production as the physical unit. In the other seven cases, total farm income (gross farm income) was the measure selected.

Dairy farming, unlike other agricultural productions, has by-products. First and foremost, dairy cattle sales from culled cows, male calves and heifers not retained as replacements. In some countries, as in NZ, some male calves may be fattened on-farm and later sold. Second, some farmers produce their own feed (silage) and harvest grass surplus (forage). Both can be a source of revenue.

Using farm income as the output variable has the disadvantage that inefficiency estimates may reflect not only technical efficiency, but allocative efficiency as well, a problem acknowledged by few authors (Jaforullah and Devlin, 1996).

Misleading estimates of efficiency can be obtained if output is measured in physical units but farms in the sample do not derive most of their income from dairy. One possibility is to correct input use by the share of dairy revenue or to restrict the sample to dairy farmers that derive most of their income from dairy. Mbaga, Romain, Larue and Lebel (2003) addressed the issue by restricting their sample to farmers who derive at least 80% of their revenue from dairy activities.

Labour input was introduced in all the studies. Eleven studies measured it in physical units (total hours worked, total labour equivalent units) and five in monetary units. Each approach has its drawback. When labour is imputed in physical units, no distinction about the quality of labour can be made within the labourers in a farm and across farms. Moreover, it is implicitly assumed that family and hired labour are equally productive. When labour is measured in monetary units, it better reflects the quality of hired workers but a value for family work has to be imputed.

Capital is the second input included most commonly. In eleven cases, capital input was not aggregated with other inputs. Three studies measured capital as total stock of capital (including land and improvements), while six used the "opportunity cost of capital" approach to measure it. They include depreciation, maintenance, insurance and interest on different types of capital. Some considered buildings and machinery, while others machinery only. A special case is Piesse, Thirtle and Turk (1996), where the service flow of capital was calculated by adding depreciation on buildings and machinery and running costs (fuel, electricity, repairs). Regarding this approach, comprehensive and disaggregated information is needed to allow for the application of differential depreciation rates.

One study (Battese and Coelli, 1988) measured capital as the replacement value of plant and equipment depreciated by age, and another (Kumbhakar, Ghosh and McGuckin, 1991) used total dairy machinery hours corrected by horsepower as a proxy of capital. Ahmad and Bravo-Ureta (1996) included depreciation on building and equipment under miscellaneous expenses. In the remaining five cases, a measure of capital input was not included, although Cuesta (2000) used number of cows as a proxy of capital.

Feed input, included in ten studies, is the next most commonly used input. Units of measurement differ markedly among studies. Some studies measured feed in physical units and differentiated between concentrate and forage. Others only include expenditure on feed (i.e., "imported" feed). Finally, some studies used total cost on feed and combine the expenditure on imported feed and the cost of homegrown feed.

Number of milking cows was included in seven studies. Total dairy herd was used as an input variable in one study, as the authors considered that it reflected better the output measure they were using (total farm income) (Jaforullah and Devlin, 1996).

Land was included in physical units in four studies. Dawson (1985) and Dawson and White (1990) used rental value of land. In two other cases, land was included in the total stock of capital (Hallam and Machado, 1996 and Jaforullah and Devlin, 1996)

Finally, animal expenses (veterinary, breeding and other animal expenses) and crop expenses (fertilizer, seed, repairs and maintenance, fuel) are mentioned three times each.

DEA allows for the inclusion of multiple outputs. This possibility is very helpful in dairy farming, where several sources of revenue are present. However, most of the studies (six) included single output (milk) measured either in physical units or in monetary units. Only two studies adopted a multiple output approach.

Labour input was incorporated in all the studies that applied DEA. Seven of the studies measured labour in physical units and only one measured labour in monetary units.

Capital was included as an input in six cases. Three of the studies measured capital as the total value of assets. The other three studies adopted the capital cost approach, albeit using different ways to estimate it: 4% of all capital locked up in production (including land); interest paid plus return on equity multiplied by equity and intermediate inputs plus service flows from stock of genuine capital items.

Feed input was included in five studies. Similar to the stochastic frontier studies, type of feed considered (forage/concentrate; "imported"/home-grown) and units of measure (physical/monetary) differ markedly. One interesting case is Fraser and Cordina (1999) that measured supplementary feeding in megajoules of metabolise energy (MJME) to reflect differences in energy content.

Cows were included in four cases. Measurement units were physical or monetary. One study used an adjusted measure of milking cows to account for differences in breed and age distribution of the herd.

Total area, as an input, was used in five studies. Unlike the studies that applied the stochastic frontier approach, total area was measured in physical units, and only two of them adjusted area by quality (Mathijs and Vranken, 2001) or perennial pasture equivalent (Fraser and Cordina, 1999).

Finally, animal expenses (veterinary, breeding and other animal expenses) were used as an input in three studies and fertilizer (expenditure on, or total volume applied) in two studies.

As previously mentioned, the availability and reliability of data largely dictates the selection of variables to estimate the frontier. This was confirmed by the vast selection of the input/output sets found. None of the authors claimed superiority of one input/output arrangement over other. Similarly, as was said before, none of the authors considered the possibility that different ways of aggregate inputs may yield different efficiency estimates within the same sample. For example, some farms may not renew pastures or use homegrown silage. Therefore, an aggregate measure of input like "crop expenses" may not give due weight to these differences.

3.2.3 Determinants of inefficiency

Of the twenty-four studies reviewed, only four of them went further and investigated the determinants of (in)efficiency (Table 3.7). This is cause for concern, as determination of the causes of inefficiency is crucial; it is the building block of future actions to help farmers enhance their profitability by way of improving efficiency in resource use. However, gathering adequate data on possible determinants of inefficiency may be harder to achieve.

Additionally, six studies reported interesting findings about the relationship of technical efficiency and some exogenous variables (Ahmad and Bravo-Ureta, 1996; Bravo-Ureta, 1986; Bravo-Ureta and Rieger, 1990 and 1991; Dawson, 1985 and Kumbhakar, Biswas and Bailey, 1989). None of these papers assumed causality, but they mentioned some associations and/or correlations between some of the variables used and technical efficiency.

Ahmad and Bravo-Ureta (1996), based on the fixed effect estimator results, reported a significant inverse relationship between technical efficiency and herd size. They also found a strong and positive correlation between technical efficiency and "concentrate per cow" and "other expenses per cow," and a positive but weak relationship with "animal expenses per cow" and "crop expenses per cow" and "labour per cow." Bravo-Ureta (1986), using a Chi-square test, accepted the hypothesis that herd size and technical efficiency were statistically independent variables.

Bravo-Ureta and Rieger (1990) divided the sample farms into three groups and used ANOVA and Kruskal-Wallis tests to analyze the relationship between socioeconomic characteristics and technical efficiency (TE), allocative efficiency (AE) and economic efficiency (EE). Results indicate that herd size and extension are positively related with TE, and negatively related with AE and EE. Experience, in turn, shows a negative relationship with EE and AE and no significant association with TE, whereas education does not have a significant association with efficiency.

Bravo-Ureta and Rieger (1991) found a positive but weak association between herd size and TE. They also reported a strong positive correlation between variable costs per cow and TE. Dawson (1986), in turn, reported a positive and significant correlation between TE and land size.

Finally, Kumbhakar, Biswas and Bailey (1989) reported similar findings in regard to size, i.e., large farms (by sales value) had better allocative and scale efficiencies. They also found that education had a strong and positive effect on labour and capital productivity and that off-farm income affected efficiency negatively.

The following studies examined the determinants of (in)efficiency; Hallam and Machado (1996); Kumbhakar, Ghosh and McGuckin (1991); Mathijs and Vranken (2001) and Weersink, Turvey and Godah (1990).

Hallam and Machado (1996) investigated the relationship between technical efficiency estimates obtained by the Haussam-Taylor method and some farm characteristics using a simple OLS regression. They reported a positive association between size (measured in farm value added) and technical efficiency.

Non-specialised[7] farms appear to be more efficient than specialised ones. Intensiveness in milk production is measured by feed per cow (positive and significant) and land per cow (positive but not significant). The stock of machinery and equipment per cow that was considered a proxy of capital-intensive production technology was positive but not significant. Evidence that family farms are more efficient than entrepreneurial farms is not conclusive. Finally, they introduced dummies for location (coastal vs. inland), altitude and handicapped zones, to determine whether technical efficiency is influenced by these factors. Results were conflicting, as one region that should appear to be less efficient turned out to be more efficient. However, as the estimates of technical efficiency obtained were relative to a common frontier, location differences in efficiency may have masked different technologies.

Kumbhakar, Ghosh and McGuckin (1991) developed a single step procedure to estimate determinants of inefficiency. They assumed that technical inefficiency has a deterministic and a stochastic component and used farm-specific exogenous variables to explain the former. Before this single step procedure, most researchers investigated the determinants of technical inefficiency on a two-step approach. In the first step, estimates of technical inefficiency were obtained and then regressed on some farm-specific factors in the second step. Two problems were identified. First, inefficiency effects were assumed to be independently and identically distributed, while in the second step, they were not identically distributed, as they were assumed to be a function of farm-specific factors. Second, since technical inefficiency (the dependent variable) is bounded between 0 and 1, ordinary least squares may not be appropriate. They reported a positive association (causality given the methodology) between size and technical efficiency. Similarly, farms with a higher level of education have higher values of technical efficiency.

Mathijs and Vranken (2001) used a Tobit regression model (as efficiency scores are truncated) to assess the sources of measured efficiencies. Farm-specific estimates of

[7] Specialised and non-specialised refer to the share of dairy income in total farm income.

technical efficiency were used as the dependent variable and regressed on different explanatory variables. They performed the analysis for family farms, corporate farms and for the pooled data. Overall, they did not find a significant difference in technical efficiency between family and corporate farms.

Mathijs and Vranken (2001) also reported a positive impact of education on technical efficiency for family farms. However, for corporate farms, human capital does not explain much of the differences in technical efficiency. This finding, although intriguing at first sight, is somehow expected. Corporate farms are able to select and hire human capital from a larger and more homogeneous pool. Conversely, family farms rely on at-home human capital. Hence, differences in human capital between family farms are amplified vis-à-vis those of corporate farms. For family farms, age has a negative effect on efficiency. Size as measured by total output, as well as specialisation, has a positive effect on efficiency both for family and corporate farms.

Interestingly, Mathijs and Vranken (2001) found that off-farm work has a positive impact on efficiency, whereas Kumbhakar, Biswas and Bailey (1989) reported a negative association, which occurred because less time is spent on managerial activities improving farm efficiency. Mathijs and Vranken (2001) proposed an alternative view by suggesting that time off-farm allows information to be acquired that improves farmers' managerial skills. Both results may be correct. The knowledge base of Utah dairy farmers (Kumbhakar, Biswas and Bailey, 1989) may be such that loosening of managerial activities cannot offset the benefits of acquiring extra information, whereas the reverse may be applicable to Hungarian dairy farmers.

Weersink, Turvey and Godah (1990) also used a two-step approach to investigate factors affecting inefficiency. Given the independent factors, they used a censored regression to predict efficiency. Their model explains 46% of the variability in the overall technical efficiency. As in other studies, they found that herd size (measured in cows) has a positive effect on technical efficiency, but at a decreasing rate. They also reported that farming experience has a negative effect. Their explanation is based upon the assumption that younger farmers are more acquainted with advanced technologies. Milk production per cow, as well as butterfat content, has a positive effect on efficiency. The proportion of feed purchased, another management characteristic, has a negative effect on efficiency. They concluded that quality and price of homegrown feed is better than that of purchased feeds. Debt to asset ratio, building per cow and horsepower of the largest tractor all have negative coefficients, implying that farms may be operating at less than full capacity and are overcapitalised.

Finally, two other findings from Weersink, Turvey and Godah (1990) are worthy of mention. First, farm efficiency was found to be positively related to the infrastructure of services, which in turn is determined by the number of farms and the resource base. Second, corporate operations were not found to be more efficient than owner-operators.

3.3 Previous studies in dairy farm total factor productivity

Six studies focused their attention on dairy farm productivity (Tables 3.2 and 3.8).

Productivity change is defined as the ratio of change in output to change in input. In the hypothetical case of a production unit using one input to produce one output, the measure of productivity is fairly simple to derive. However, production units use several inputs to produce one or more outputs, and under such circumstances, the primary challenge in measuring TFP results from the need to aggregate the different inputs and outputs. The aggregation of inputs and outputs is both conceptually and empirically difficult. Several methods to aggregate inputs and outputs are available, resulting in different approaches to measuring TFP. Such methods can be classified into three major groups: (a) econometric production models; (b) TFP indices; and (c) frontiers models (Coelli, Rao and Battese, 1998). Methods in (a) and (b) are called non-frontier approaches to TFP measurement, as it is not necessary to identify the frontier of potential attainment. In contrast, frontier models do require the estimation of the production frontier. Further classification of TFP measurements is again done along non-parametric (index number) models and parametric (econometric approaches) models. Grosskopf (1993) provides a survey on productivity measurement and Hulten (2001) provides an excellent biography on productivity growth.

The approaches used to estimate TFP cover a vast range of methodologies, from index numbers (Anderson and Johnson, 2002) to distance functions (Brümmer, Glauben and Thijssen, 2002).

Table 3.2 - Summary of productivity studies in dairy farming

Author(s)	Methodology	Objective
Ahmad and Bravo-Ureta (1995)	Econometric	Decompose production growth into technical change, technical efficiency change and input-growth
Anderson and Johnson (2002)	Index numbers	Analyze trends in productivity growth
Brümmer, Glauben and Thijssen (2002)	Econometric	Decompose TFP index into technical change, technical efficiency change, allocative efficiency regarding inputs and outputs, and scale component
Kumbhakar and Hjalmarsson (1993)	Econometric	Examine technical efficiency and technical progress, after separating inefficiency from farm-specific effects
Tauer (1998)	Non-parametric	Decompose TFP index into technical change and technical efficiency change, adjusting for apparent regressive technology
Piesse, Thirtle and Turk (1996)	Econometric Non-parametric Index numbers	Study effects of ownership and control on productivity

Anderson and Johnson (2002) and Piesse, Thirtle and Turk (1996) applied index number to estimate TFP on dairy farming in NZ and Slovenia respectively. The index number approach to measure TFP is a non-parametric non-frontier approach.

TFP index is calculated from output and input indexes, which in turn are aggregations of detailed accounts of inputs used and outputs produced. Growth accounting represents a technique for estimating the contribution of different factors to economic growth. With the aid of marginal productivity theory, growth accounting decomposes the growth of output into growth of labour, land, capital, education, technical knowledge and other miscellaneous sources (Diewert and Lawrence, 1999; OECD, 2001 and Raa and Mohnen, 2002).

The theory of index numbers is uniquely crucial to the aggregation of inputs and outputs. Three examples of indexes are Laspeyres index, Fisher index and Tornqvist index that approximates the Divisia index. The Laspeyres indexing procedure is believed to be exact for (or imply) a linear production function in which all inputs are perfect substitutes in the production process. Similarly, the Tornqvist index is concerned with the natural discrete approximation of productivity growth and is said to be exact for (or imply) a translog production function. Fisher index exacts Cobb-Douglas production function (Coelli, Rao and Battese, 1998 and Diewert and Lawrence, 1999).

The use of index numbers imposes several strong assumptions about technology (Hicks-neutral technical change, constant returns to scale and long-run competitive equilibrium). Notable shortcomings of the non-parametric non-frontier approaches include biased estimates of productivity growth because of the prevalence of inefficiency. Also, in the presence of allocative inefficiency, TFP index would be biased. It is likely that farmers are not using the various factors of production in the best proportions given the input prices, i.e., allocative inefficiency. Hence, using input shares to aggregate inputs also biased the TFPG estimates. Another disadvantage is that since index numbers are not statistically derived, statistical methods cannot be used to evaluate their reliability. Additionally, they have not been particularly informative in identifying sources of growth. Their advantage, of course, is that they can be derived regardless of the number of observations and hence they are relatively easy to calculate (Balk, 2003; Coelli, Rao and Battese, 1998; Grosskopf, 1993 and OECD, 2001).

Kumbhakar and Hjalmarsson (1993) developed a method to separate technical inefficiency from farm-specific characteristics (location, climate and land quality). Under this framework (based on a fixed effects production function), they examine technical efficiency change and technical progress at the frontier.

Ahmad and Bravo-Ureta (1995) used the same framework, but alternative methods of estimation, fixed effects and ML. Technical efficiency was assumed to be time varying and time invariant, and in the case of ML estimation, to follow a half-normal and truncated normal distribution.

They estimate a Cobb Douglas (CD) production function and decomposed output growth in technical progress plus changes in technical efficiency plus a size effect. Unlike

Kumbhakar and Hjalmarsson (1993), who allowed for non-neutral technical progress, Ahmad and Bravo-Ureta (1995) considered neutral technical change, using the coefficient on the time trend as a proxy for technical progress or time dummy variables (in the FE model). As a proxy for the size effect, they computed the difference in input use by each farm between periods. Technical efficiency change was estimated as the difference in technical efficiency of each farm between periods. The sum of the three components results in the output growth over the period considered.

Brümmer, Glauben and Thijssen (2002), Tauer (1998) and Piesse, Thirtle and Turk (1996), in turn used the distance function approach to measure TFP. Distance function, input- or output-orientated, is an alternative way (to production, cost or profit functions) to represent a technology. An output distance function measures the maximal proportional expansion of the output vector, given an input vector. Similarly, an input distance function considers the minimal proportional contraction of the input vector, given an output vector. The main advantages of representing a technology with a distance function is that multi-input multi-output production technology can be described and, as information on prices is not necessary, there is no need to specify a behavioural objective (like cost minimization or profit maximization). Distance functions can be computed by different methods: DEA, parametric deterministic linear programming, corrected ordinary least squares or SFA. (See Coelli, Rao and Battese (1998) for the theoretical underpinnings of distance functions and Coelli and Perelman (1999) (2000) for estimation methods.)

Tauer (1998) and Piesse, Thirtle and Turk (1996) estimated productivity using the non-parametric MPI. The Malmquist index is defined using distance functions. The estimation of the distances required to gauge TFP is computed within the DEA framework (Coelli, Rao and Battese, 1998). The main advantage of using DEA for the estimation of distance functions is that it does not require the specification of a functional form to the technology. Conversely, Brümmer, Glauben and Thijssen (2002), using a stochastic frontier approach, assumed a translog functional form for the parametric distance functions. The distinctive feature of their model is that they explicitly account for allocative efficiency regarding inputs and outputs to the decomposition of the TFPG index. Hence, they were able to decompose TFPG into technical change, technical efficiency change, allocative efficiency regarding inputs and outputs and scale component.

Caves, Christensen and Diewert (1982) introduced the MPI as a theoretical index based on distance functions (Coelli, Rao and Battese, 1998). Distance functions are functional representations of multiple-output, multiple-input technologies, which require data only on input and output quantities (Coelli, Rao and Battese, 1998 and Färe et al., 1992). This distance function was later incorporated into the production theory lending its use to the measurement of productivity. More importantly, the distance function on which the MPI is based happens to represent a value that is the inverse of technical efficiency defined by Farrell (1957). As a consequence, methodologies for technical efficiency measurement (like DEA or stochastic production frontiers) can be employed directly to calculate the MPI.

The Malmquist TFP index is closely related to several other productivity indexes that have been proposed in the literature. For instance, the MPI is more general and includes the Törnqvist and Fisher indexes as its special cases (Coelli, Rao and Battese, 1998). It has been shown that the MPI is equivalent, under rather strong assumptions (technology is translog, second order terms are constant over time, firms are cost minimizers and revenue maximizers) to the Törnqvist index (Färe et al., 1994), which is the discrete counterpart of the Solow growth accounting model (Coelli, Rao and Battese, 1998). The Törnqvist index does not require estimation of distance functions, but rather aggregates inputs and outputs by weighting them by their shares (Diewert and Lawrence, 1999). As such, the MPI forms the basis for the Törnqvist and Fisher indexes. While the computation for the Törnqvist and Fisher indexes does not involve estimating distance functions and is thus less demanding, the MPI is much more instructive due to its capability of separating and identifying distinct sources for explaining productivity growth (Färe et al., 1994).

Finally, it is worth mentioning studies by Cuesta (2000), Heshmati and Kumbhakar (1994) and Kumbhakar and Heshmati (1995). Even though the focus of attention of these studies relied on alternative assumptions about the inefficiency term, they estimated neutral technical progress. Meanwhile, Cuesta (2000) used time dummy variables and Heshmati and Kumbhakar (1994) and Kumbhakar and Heshmati (1995) captured the shift in the production frontier using time as a regressor.

3.3.1 The underlying assumption about technology

Studies by Ahmad and Bravo-Ureta (1995), Kumbhakar and Hjalmarsson (1993) and Piesse, Thirtle and Turk (1996) have been discussed in section 3.2.1.

With the exception of Brümmer, Glauben and Thijssen (2002), all the studies reviewed in this section assumed that farms operate under the same technology. Given that they compared countries, which among other things have different agricultural policy regimes, they estimated separate distance function for each country and a common frontier function (pooling the observations from all countries). The null hypothesis that all countries were operating under the same technology was rejected using the likelihood-ratio test. This common or pooled frontier helps to ascertain the potential for improvement by adopting a hypothetical best-practice for all countries.

Tauer (1998) implicitly assumed that all farms operate under the same technology. This assumption may not be warranted on two counts. First, Kumbhakar, Ghosh and McGuckin (1991) demonstrated that small, medium and large Utah dairy farmers did not operate under the same technology. Second, Tauer (2001) found that for a sample of New York dairy farms, the costs of production (per kg milk) decreases with herd size. This in turn may be masking differences in technology applied among herds of different sizes.

3.3.2 The input/output variables used

Similar to the studies on efficiency, the output-input variables selected and particularly the aggregation of them is dictated by the databases and the interest of the researchers in checking the behaviour of some inputs or aggregation of them (Table 3.8). For example, Tauer (1999) considered an energy input (fuel and electricity) separately because of the increasing concern about the efficiency in energy use (p 248).

Output was measured as milk volume in three papers. The other three papers used a quantity index of milk, an aggregate quantity index of all output produced and milk sales as output. Two studies included an aggregate measure of other outputs produced. The difference between both studies in the aggregation procedure relies on the price index used to deflate the value of each output. Meanwhile, Brümmer, Glauben and Thijssen (2002) used individual prices received by farmers (where possible) to construct the index. Tauer (1999) used the same official price index for all farms.

Regarding input variables, labour was included in all cases and always measured in physical units (hours or worker equivalent). Capital input was considered in five studies and measured in different ways. Anderson and Johnson (2002) and Kumbhakar and Hjalmarsson (1993) used the capital user cost approach. The study by Kumbhakar and Hjalmarsson (1993) included land and buildings, while the study by Anderson and Johnson (2002) only considered depreciation and interest on the stock of capital equipment. Piesse, Thirtle and Turk (1996) estimated the service flow of capital by adding depreciation on building and machinery and running costs (fuel, electricity and repairs).

Brümmer, Glauben and Thijssen (2002), in turn, presented an aggregate measure of stock of capital (building, equipment and livestock deflated by their corresponding price index). Finally, Tauer (1999) included capital input using the cost approach, but under two different input aggregations: crop input (depreciation, repairs and interest on machinery) and real estate input (depreciation, repairs and interest on buildings plus fencing costs).

Total area measured in physical units was used in three studies. Animal expenses (veterinary, breeding and other animal expenses) were used as an input on two occasions as well as crop expenses (fertiliser, seed and repairs and maintenance on machinery). Feed input was used twice, measured in physical units (concentrate in tons) and as expenditure on feed (i.e., “imported” feed).

3.3.3 Determinants of inefficiency

None of the six studies went further and investigated the determinants of (in)efficiency. Ahmad and Bravo-Ureta (1995), based on the results obtained from the fixed effects estimation method, explored the correlation between annual rate of growth in milk production and herd size, input use per cow and technical efficiency. They reported a significant positive relationship between annual rate of growth in milk production and herd size, and with some inputs per cow (concentrates, crop expenses and animal expenses), and a weak correlation with “other expenses per cow” and technical efficiency. “Labour per cow" and the annual rate of growth in milk production exhibited a negative but non-significant association.

Technical efficiency, in turn, showed a strong positive correlation with "concentrate per cow" and "other expenses per cow," and a positive but non-significant relationship with "animal expenses per cow" and "crop expenses per cow." Conversely, technical efficiency and "labour per cow" showed a weak but negative correlation. Finally, Ahmad and Bravo-Ureta (1995) found a significant inverse relationship between technical efficiency and herd size, but a positive and significant association between the rate of change in technical efficiency and herd size.

3.4 Concluding comments

Twenty-eight studies focusing on efficiency and productivity of dairy farming were reviewed. The review was done along three main lines not explored before: the underlying assumption about technology, the input/output variables introduced in the production function and the exogenous variables used as determinants of technical inefficiency among farms.

Three studies (Brümmer, Glauben and Thijssen, 2002; Hallam and Machado, 1996 and Kumbhakar, Biswas and Bailey, 1989) investigated whether technology applied differed across dairy farms. The reasons behind the assumption that farmers operated under different technologies were different. Brümmer, Glauben and Thijssen (2002) tested whether dairy farmers in three different countries (Germany, Poland and the Netherlands) operated under the same technology, i.e., they faced the same frontier. Hallam and Machado (1996), in turn, analysed whether differences might arise due to ownership structure. Kumbhakar, Biswas and Bailey (1989) related them to farm size. As mentioned in section 1.7, the present study will investigate whether technology applied differed across dairy farms given to location.

As shown by the literature review, no single study attempted to check the robustness of efficiency estimates to input/output variable selection. As Bravo-Ureta (1986) cautioned, aggregation of inputs and outputs poses a limitation on production function analysis. The database obtained for the present study has an ample dis-aggregation of inputs, allowing any limitations imposed by input aggregation to be assessed.

For the empirical analysis, the Malmquist index was used to estimate TFPG. The MPI, introduced by Caves et al. (1982) and based on distance functions, has become extensively used in the measure and analysis of productivity (Brümmer, Glauben and Thijssen, 2002; Kim and Han, 2001; Tauer, 1998 and Piesse, Thirtle and Turk, 1996). The reasons for choosing the MPI over the Törnqvist and Fisher indexes are numerous. First and foremost, the MPI can be decomposed into two components for explaining productivity sources: technical change and technical efficiency change (Färe et al., 1994). Second, the MPI does not require price data (it is based only on quantity data). Third, the MPI is capable of accommodating multiple inputs and outputs without worrying about how to aggregate them. Fourth, the MPI does not make any restrictive value/behaviour assumptions for the economic units like cost minimization or profit maximization, as required by the Törnqvist and Fisher indexes (Coelli et al., 1998; Grifell-Tatjé and Lovell, 1996). Therefore, this allows for gaining insight into the sources of productivity growth at a regional level. This in turn will allow comparing and assessing the relative importance of both sources of growth at a regional level. Further, the MPI will be calculated using methodologies for technical efficiency measurement (like DEA or stochastic production frontiers) providing, therefore, farm-level estimates of productivity growth, technical efficiency change and technical progress to guide on-farm improvements.

Finally, the meagre attention given to the understanding of the causes of inefficiency in the literature is surprising. This type of information is vital for policy and extension purposes. Extension agencies would benefit, as it would help to target those farmers in need of assistance, thereby reducing the cost of extension programs. Policy makers in turn would gain insight in evaluating the impact of changes in sectoral policy (e.g., reduction of internal support) or national trade policy (e.g., reduction in tariff barriers that expose farmers to international competition). Regrettably, the database has no relevant information to address this issue. Advancing into the recommendations and areas for further research, future data collection needs to address this weakness.

Table 3.3 - Studies that applied econometric methods

Authors	Methodology	Input/output variables
Ahmad and Bravo-Ureta (1996) Vermont dairy farms (US)	Fixed effects production functions and stochastic production frontiers with time varying and time invariant efficiency	Output: Milk production (in hundredweight adjusted to a 3.5% butterfat basis) Inputs Number of dairy cows Total labour in worker eq. Purchased concentrate (tons) Animal expenses (veterinary, breeding and other animal expenses) Crop expenses (fertiliser, seed, repairs and maintenance, fuel) Other expenses (electricity, depreciation and miscellaneous)
Battese and Coelli (1988) Victoria and New South Wales dairy farmers (Australia)	Stochastic frontier production function (FPF)	Output: Total gross farm returns Inputs Value of total farm labour Value of total cost of fodder, seed and fertiliser Value of the capital (average estimated replacement cost of structures plant and equipment depreciated by age)

Bravo-Ureta (1986) New England dairy farmers (US)	Deterministic FPF probabilistic frontier approach Estimated by linear programming	<u>Output</u>: Milk production (in hundredweight adjusted to a 3.5% butterfat basis) <u>Inputs</u> Number of dairy cows Total labour in worker eq. Consumption of purchased concentrate (tons) Annual machinery capital services (depreciation, and repairs and maintenance on machinery and equipment in dollars) Dummy for breed (1= Holstein, 0 otherwise)
Bravo-Ureta and Rieger (1990) New England and New York dairy farmers (US)	FPF models: Deterministic (estimated by LP, COLS and ML) Stochastic (estimated by ML)	<u>Output</u>: Milk production (in hundredweight adjusted to a 3.5% butterfat basis) <u>Inputs</u> Total labour in worker eq. Consumption of purchased concentrate (tons) Animal expenses (veterinary, breeding and other animal expenses) Crop expenses (fertiliser, seed, repairs and maintenance, fuel)
Bravo-Ureta and Rieger (1991) New England dairy farmers (US)	Stochastic FPF to derive stochastic cost frontier that was subsequently decomposed in economic and allocative efficiency	<u>Output</u>: Milk production (in hundredweight adjusted to a 3.5% butterfat basis) <u>Inputs</u> Annual variable labour in full time worker eq.

		Consumption of purchased concentrate (tons) Consumption of forage feed corrected by dry matter (tons) Milking technology (stanchion barn and a bucket and carry milking system=1; 0) Farm location (Maine, Massachusetts=1; 0) and (Vermont=1; 0)
Cuesta (2000) Dairy farms from Asturias region (northern Spain)	Stochastic FPF that allows for firm-specific temporal variation in technical efficiency	<u>Output</u>: Milk production (thousand litres per year) <u>Inputs</u> Total labour in full time worker eq. Land (total farm area, ha) Cows (average number of milking cows) Feedstuffs (only concentrate to dairy cows, tons per year)
Dawson (1985) North-West of England	Deterministic Three methods: Two-step OLS Analysis-of-covariance Linear programming	<u>Output</u>: Total revenue <u>Inputs</u> Total wage bill Livestock and crop costs Machinery costs General farming costs Rental value of land

Dawson and White (1990) Dairy farms from England and Wales	Stochastic FPF Examine allocative and technical inefficiencies after production quotas were introduced	Output: Milk output (litres) Inputs Total labour cost Concentrate costs Forage costs Rent (on land) Machinery costs Herd replacement costs
Hallam and Machado (1996) Dairy farms in northwest Portugal	FPF Four approaches to estimate parameters: Within estimator Variance component (GLS) Haussman-Taylor Maximum Likelihood Estimator	Output: Value of total gross farm production Inputs Number of milking cows in equivalent units Total labour in equivalent units Value of total feed consumed (purchased plus self-produced (p+s-p) Total consumption of intermediate inputs: seed, fertilizer, energy, etc. (p+s-p) Capital stock (land and buildings, plant, machinery, equipment and circulating capital)

Heshmati and Kumbhakar (1994) Swedish dairy farms	SPF, within transformation and ML Assumes technical inefficiency to be farm- and time-specific Separates farm-specific effects (assumed to be time invariant) from technical efficiency (time varying) Estimation through multi-step procedure	Output: Total farm income Inputs Number of milking cows Total labour cost (family plus hired workers) Cost of concentrate fodder (purchased plus self-produced) Capital, user cost (depreciation, maintenance, insurance and interest) Miscellaneous (fertiliser, purchased cows, etc. use in dairy production) Regional dummies Size dummies
Jaforullah and Devlin (1996) New Zealand dairy farms	Stochastic FPF Three possibilities regarding the distribution of inefficiency	Output: Total dairy farm revenue Inputs Total dairy herd Total worker-hours per week (based on full time labour eq. units) Animal expenses (health, breeding and herd testing) Feed supplements expenditure (silage, hay, meal and grazing-off) Fertiliser expenditure Capital (closing book value of fixed assets, including land and buildings)

Kumbhakar, Biswas and Bailey (1989) Owner-operated dairy farms in Utah (US)	Stochastic FPF system With endogenous and exogenous variables Decomposition of inefficiency into estimate technical, allocative and scale inefficiencies	Output: Milk production (pounds) Inputs: Total hrs worked (family plus hired workers) Capital, op. costs (depreciation and interest expenses on all capital) Land (ha) Exogenous variables: Education (operator) Off-farm income Dummies for size
Kumbhakar, Ghosh and McGuckin (1991) US dairy farms	Stochastic FPF Estimation ML based on a simultaneous system of equations To study profitability in relation to RTS and economic efficiency To identify determinants of inefficiency	Output: Milk production (in hundredweight adjusted to a 3.5% butterfat basis) Inputs: Number of dairy cows Total labour in man hrs eq. (family plus hired workers) Capital, flow (dairy machinery hrs adjusted by number of horsepower)
Kumbhakar and Heshmati (1995) Swedish dairy farms	SPF, random effects and ML To study the persistent and residual component of inefficiency Estimation through a multi-step	Output: Total farm income Inputs: Number of milking cows

	procedure	Total labour cost (family plus hired workers) Cost of concentrate fodder (purchased plus self-produced) Cost of grass fodder (adjusted by water content) Arable land (ha) Pasture land (ha) Capital, user cost (depreciation, maintenance, insurance and interest, all capital) Miscellaneous (fertiliser, purchased cows, etc. use in dairy production) Regional dummies Age of farmer (proxy of experience) Time (proxy for exogenous technical change)
Kumbhakar and Hjalmarsson (1993) Swedish dairy farms	SPF, fixed effects and EM algorithm To separate technical inefficiency from individual specific effects Estimation through a two-step procedure	<u>Output</u>: Total sales per farm <u>Inputs</u> Total labour (family plus hired workers in hrs) Arable land, adjusted for soil quality and climatic location (ha) Capital, user cost (depreciation and interest on the stock of capital equipment) Materials, cash expenditure (fuel, seed, pesticides, repairs and maintenance of capital equipment)

Table 3.4 - Studies that applied mathematical programming techniques

Authors	Methodology	Input/output variables
Asmild et al. (2003) Danish dairy farmers	Multi-directional efficiency analysis and DEA VRS input-orientated	<u>Output</u>: Gross returns <u>Inputs</u> Building costs (book depreciation building investment plus cost of maintenance) Equipment costs (sum of book depreciation of inventory, equipment maintenance costs and contract operation costs) Capital costs (4% of all capital locked up in land, production buildings, livestock, inventory and stock) Labour costs (wages plus family labour payment) Miscellaneous costs (insurance, energy, water, etc.)
Cloutier and Rowley (1993) Quebec dairy farms (Canada)	DEA CRS input-orientated	<u>Outputs</u>: Milk production (in litres) Revenue from milk sales Other revenue <u>Inputs</u> Herd size

		Total labour in annual worker eq. Cultivated land, including rented areas (ha) Animal feed Composite of other inputs
Fraser and Cordina (1999) Irrigated dairy farms in Northern Victoria (Australia)	DEA CRS and VRS input-orientated VRS output-orientated	<u>Output</u>: Milk production (in kgs of milk fat and protein) <u>Inputs</u> Number of cows adjusted for age distribution of the herd and breed Total labour (hrs) Milking area adjusted to a perennial pasture equivalent (ha) Irrigation water applied (Megalitres) Supplementary feeding (converted into megajoules of metabolisable energy) Fertiliser (aggregate of all in tons)
Jaforullah and Whiteman (1999) New Zealand dairy farms	DEA CRS, VRS, NRS (non-increasing returns to scale) input-orientated	<u>Outputs</u>: Milk fat (kg) Milk protein (kg) Milksolids (kg) <u>Inputs</u> Total dairy herd Total area (ha)

		Total labour (hrs per week) Animal expenses (health, breeding and herd testing) Feed supplements expenditure (silage, hay, meal and grazing-off) Fertilizer expenditure Capital (closing book value of fixed assets, including land and buildings)
Mathijs and Vranken (2001) Hungarian dairy farms	DEA VRS, CRS, input-orientated	Output: Gross output (physical production valued at fixed prices and corrected for own-produced feed used for animals) Inputs Land (ha) (total cultivated area multiplied by a land quality index) Total labour annual working units (AWU) one AWU corresponds to 2,150 labour hrs or the number of hrs that a full-time worker can perform in one year Capital (estimated value of farm buildings, machinery, livestock and plantations) Intermediate inputs (expenditure on seeds, feed grains, roughage, concentrated feed, fertilisers, electric energy, gas, fuels and services plus the value of their inventories

Weersink, Turvey and Godah (1990) Ontario dairy farms (Canada)	DEA CRS and non-constant returns to scale (NCRS) input orientated Decomposition of technical efficiency into purely technical, congestion and scale efficiency	<u>Output</u>: Milk output (in hectolitres adjusted to a 3.6% butterfat content) <u>Inputs</u> Livestock expenses (health and breeding, purchased cows and bulls and associated costs) Feed, value (all feed purchased plus change in inventories plus self-produced) Machinery expense (fuel, repair, insurance, services hired and depreciation) Building expense (repairs, property taxes, rental and depreciation) Capital, cost (interest paid plus return on equity multiplied by equity) Miscellaneous expenses (telephone, water, etc.) Labour in full time eq.

Table 3.5 - Studies that applied mathematical programming and econometric methods

Authors	Methodology	Input/output variables
Mbaga, Romain, Larue and Lebel (2003) Quebec dairy farms	DEA VRS input orientated Stochastic FPF Different functional forms and distributional assumptions of inefficiency	<u>Output</u>: Milk output/cow (in hectolitres adjusted for butterfat content) <u>Inputs:</u> Feed concentrate (kg per cow) Forage (kg per cow) Total labour/full time eq. per year per cow) Capital (total value of asset per cow) Average weight (proxy for genetic merit)
Piesse, Thirtle and Turk (1996) Dairy farms from Slovenia	DEA FPF estimated through: OLS Fixed and random effects TSCS(*) model Study effects of ownership and control on productivity and efficiency	<u>Output:</u> Milk production (litres, not adjusted by fat content) <u>Inputs:</u> Total labour in hrs (without quality adjustment) Land (ha) (not quality adjusted, most sample is similar alpine terrain) Capital (Intermediate inputs plus service flows from stock of genuine capital items) (*) time series cross section

Table 3.6 - Stochastic non-parametric a *rara avis*

Authors	Methodology	Input/output variables
Haghiri, Nolan and Tran (2004) Dairy farms from Ontario and New York	Non-parametric stochastic frontier model	Output: Milk production (in hundredweight) Inputs Land (ha, total tillable area own and rented) Labour (total equivalent worker unit) Total feed cost

Table 3.7 - Studies that aim to explain inefficiency

Authors	Method employed	Determinants of inefficiency
Hallam and Machado (1996) Dairy farms in northwest Portugal	OLS regression of Haussman-Taylor technical efficiency estimates	Size (value added) Dummy for specialisation Feed/cow Land/cow Stock machinery and equipment/cow Spatial dummies Dummy for family vs. entrepreneurial Dummy for rented farms
Kumbhakar, Ghosh and McGuckin (1991) US dairy farms	Simultaneous estimation of inefficiency determinants	Dummy for size (cows) (small. medium, large) Regional dummies Dummy for education (3) Forage quality (protein content)
Mathijs and Vranken (2001)	2nd Stage Tobit regression of DEA efficiency levels	Age Education Gender Land acquisition (proxy entrepreneurial ability) Investment dummy

		Contract dummy (sales make on contract) Dummy sales (0=self-consumption, 1=sales) Specialisation (proxy farm organisation) milk in total output Feed production dummy (1=some own grown feed) Member/partner (1=one household member is a member of a cooperative or a partner in a company)
Weersink, Turvey and Godah (1990) Ontario dairy farms (Canada)	Use of censored regression to predict actual DEA level of efficiency	Herd size Herd size square Experience (years in dairy farming) Cow yield Butterfat content Paid labour (share in total) Feed purchased (share in total) Debt to asset ratio Building per cow HP large tractor Regional dummies Dummies for business organisation Dummies for milking and manure system

Table 3.8 - Total factor productivity studies in dairy farming

Author(s)	Methodology	Input/output variables
Ahmad and Bravo-Ureta (1995) Vermont dairy farms (US)	Stochastic production frontiers with time varying and time invariant efficiency, with half-normal and truncated normal distribution Fixed effects production frontier with time varying and time invariant efficiency	Output: Milk production (in hundredweight adjusted to a 3.5% butterfat basis) Inputs Number of dairy cows Total labour in worker eq. Purchased concentrate (tons) Animal expenses (veterinary, breeding and other animal expenses) Crop expenses (fertiliser, seed, repairs and maintenance, fuel) Other expenses (electricity, depreciation and miscellaneous)

Anderson and Johnson (2002) NZ dairy faming	Index numbers	<u>Output</u>: Total output index (milk sales and livestock sales deflated by their corresponding price index and then weighted by their share in total revenue to aggregate them) <u>Inputs</u> Total labour in worker eq. Total input (all purchased inputs). Each input category is deflated by its own price index, and weighted by their share in total cost to bring all components together Capital use (deflated value of farm assets, land and buildings; equipment and livestock)
Brümmer, Glauben and Thijssen (2002) Dairy farms in Germany, Netherlands and Poland	Parametric translog output distance function that allows modeling a multi-output, multi-input technology	<u>Outputs</u>: Implicit quantity index for milk Implicit quantity index for other outputs <u>Inputs</u> Total on-farm family labour (in hrs, assuming 2,200 hrs per man year) Land (ha) Intermediate inputs (concentrate, roughage, fertilizer other intermediate inputs), an implicit quantity index was estimated for each input and then aggregated Capital stock (buildings, equipment and livestock) the same procedure was used for aggregation Note: if farm-level prices where available, they were used to calculate price index

Kumbhakar and Hjalmarsson (1993) Swedish dairy farms	SPF, fixed effects and EM algorithm to separate technical inefficiency from individual specific effects.	Output: Total sales per farm Inputs Total labour (family plus hired workers in hrs) Arable land, adjusted for soil quality and climatic location (ha) Capital, user cost (depreciation and interest on the stock of capital equipment) Materials, cash expenditure (fuel, seed, pesticides, repairs and maintenance of capital equipment)
Tauer (1998) New York dairy farms (US)	Malmquist productivity index computed within the non-parametric technique (DEA)	Outputs: Milk production (in hundredweight adjusted to a 3.5% butterfat basis) Other output (sales of cows and calves, crop sales, government payments, all deflated by their corresponding price index) Inputs Total labour in physical units (units not specified) Purchased feed (grains and concentrate, non-dairy feed, roughage) Crop (Fertiliser, seed, chemicals, machinery depreciation, interest on machinery, machinery repairs and parts, machinery hire) Livestock (purchased animals + interest on livestock, health and breeding, telephone insurance, marketing expenses and miscellaneous) Real estate (cash rent, building depreciation, interest on real estate, building and fence repair, real estate taxes)

Piesse, Thirtle and Turk (1996) Dairy farms from Slovenia	Malmquist-DEA Time Series Cross Section model	<u>Output:</u> Milk production (litres, not adjusted by fat content) <u>Inputs:</u> Total labour in hrs (without quality adjustment) Land (ha) (not quality adjusted, most sample is similar alpine terrain) Capital (Intermediate inputs plus service flows from stock of genuine capital items)

CHAPTER 4

4 A review of methods and materials used in the present study

4.1 Introduction

The chapter is divided into five sections. Section 4.2 intends to give a concise review of the concepts and definitions of efficiency and productivity, as well as to explain the relevance of such measures for benchmarking and monitoring. In section 4.3 the principal methods of estimation of efficiency and productivity are introduced and compared. Section 4.4 fully describes the methodology to be applied in the analysis of the database. The database is introduced in section 4.5 and the variables selected in section 4.6. The final section, 4.7, fully describes the models to be applied in the analysis of the database.

4.2 Concepts and definitions

Assessing the performance of a firm can be done by comparing it to a set of similar firms. This analysis is called benchmarking. Similarly, the researcher may be interested in monitoring a firm, i.e., to assess its performance of a firm over time. When both activities, benchmarking and monitoring, are undertaken together the researcher is concerned with monitoring a group of firms over time. The selection of a performance measure to undertake interfirm and intertemporal comparisons depends on the objective of the exercise. Most frequently, such comparisons use productivity measures.

There are many different types of "productivity measures." The choice among them depends on the purpose of the productivity measure as well as on the availability of data. Broadly, productivity measures can be classified into three main categories. First, single or partial factor productivity (PFP) measures, which refer to the output attributable to a single input, e.g., milk/cow. Second, multifactor productivity (MFP) measures that relate a measure of output relative to a bundle of inputs, customarily capital and labour (OECD, 2001). Finally, we refer to TFP, or simply "productivity," when all factors of production are involved. Therefore, TFP is the most comprehensive measure of productivity as it ideally includes all inputs used in the production process and all outputs produced (Diewert and Lawrence, 1999).

Productivity - a measure of the efficiency of transformation of input(s) into output(s) within a production process, and hence the ratio of the output(s) that a firm produces to the input(s) that it uses (Diewert, 2001; Diewert and Lawrence, 1999; Coelli, Rao and Battese, 1998 and Hulten, 2001 for a biography of TFP).

Both partial and multifactor productivity measures have an important weakness, because not only do they not account for all the inputs used in production (OECD, 2001), but also because they will capture output changes attributable to levels of other inputs not included in those whose productivity is being calculated (Rae and Hertel, 1998). Craig and Harris (1973) cautioned about the fallacies of focusing on partial productivity measures, because the costs associated with increases in partial productivity is often ignored. Therefore, PFP or MFP will be biased measures of TFP, with the direction of the bias unknown in the absence of information about the degree of input substitution (Coelli, Rao and Battese, 1998; Diewert and Lawrence, 1999 and Rae and Hertel, 1998).

In production economics, the process of transformation of inputs into outputs is described by a production function (Coelli, Rao and Battese, 1998 and Green, 1997). The so-called "production function"—which depicts the relationship between inputs and outputs—represents the available technology faced by the firm or industry (Balk, 2003; Greene, 1997).

Technology - the state of knowledge concerning ways of converting resources (inputs) into outputs (Griliches, 1987 and Metcalf, 1969)

Conceptually, the "industry" production function determines the frontier of potential attainment for given input combinations (Førsund and Sarafoglou, 2002), and hence the denomination of "production frontier" or "frontier function."

Production function (frontier) - the maximum set of output(s) that can be produced with a given set of inputs. Synonymous with production frontier, the technically efficiency part (outer bound) of a feasible production set, which is defined as the set of all input-output combinations that are feasible (but not necessary efficient) (Coelli, Rao and Battese, 1998).

Farrell (1957) first envisioned the existence of a production frontier when he observed that:

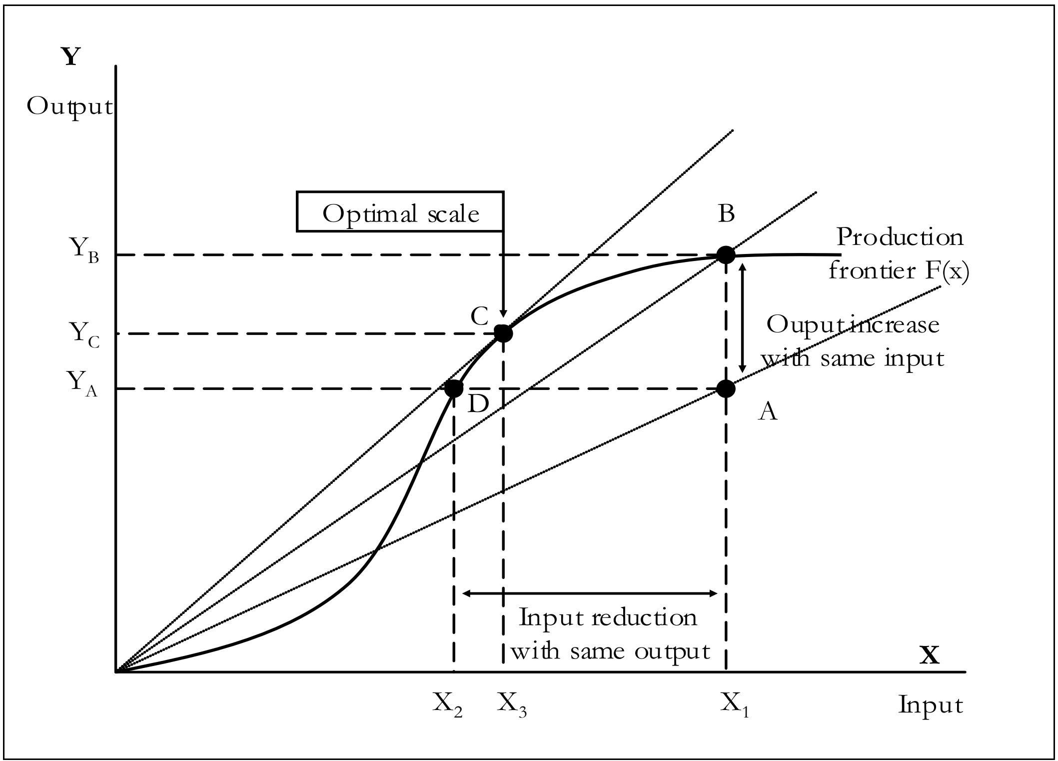
> There exists some efficient function, from which all the observed points deviate randomly but in the same direction (p 263).

He defined technical efficiency as the success of a firm in "producing maximum output from a given set of inputs." Hence, a firm that is technically inefficient can increase its output level without absorbing further inputs, thereby increasing its productivity (TFP).

Technically efficiency (full efficiency) - in an engineering sense, this means a production process has achieved the maximum amount of output that is physically achievable with current technology and given a fixed amount of inputs (Diewert and Lawrence, 1999).

Productivity and technical efficiency are different concepts (Figure 4.1). The production function F(x) represents the maximum potential attainment for given input combinations (the production frontier). The slope (Y/X) of the ray through the origin to any data point measures the productivity of the firm at that point. Imagine one firm at point A, producing output quantity Y_A with input quantity X_1. At point A, productivity is equal to Y_A/ X_1. Given input X_1 the firm is inefficient because it could be operating at point B, by producing output quantity Y_B. At point B, productivity is equal to Y_B/ X_1. It can be seen that the slope at point B is higher than at point A, hence the firm is increasing its productivity without absorbing further resources. Similarly, the firm may choose to operate at point D, decreasing input use and maintaining output constant. Again, the slope at point D is higher than that at point A, and productivity has been increased by a reduction in resources but no change in output (Figure 4.1).

Figure 4.1 – To illustrate productivity, technical efficiency and scale economies



Source: Coelli, Rao and Battese (1998)

However, at points B or D the firm is still not achieving the optimum productivity. At point C, the ray is tangent to the production frontier and hence the slope is highest. By moving along the production frontier from any of these points B or D to point C, the firm is achieving the point of maximum possible productivity. The firm is exploiting scale economies. This explains why achieving technical efficiency is so important: if the firm does not attain technical efficiency, resources are being wasted (Diewert and Lawrence, 1999).

A digression: as Farrell (1957) recognised, it is also necessary to measure "the extent to which a firm uses the various factors of production in the best proportions," given their prices or "price efficiency" (Farrel, 1957). In effect, not all combinations of inputs are equally profitable, even though they may be equally (technical) efficient. Allocative efficiency refers to the production of a given output at minimum costs by selecting the best input mix, given their prices. Farrell (1957) defined overall economic efficiency as the combination of price (allocative) and technical efficiency. It should be mentioned that allocative efficiency estimation is only possible when the firm's input prices are known.

As stated above, when technical efficiency is not attained, resources are being physically wasted. Given technical efficiency, if allocative efficiency is not attained, profit is being wasted. Furthermore, Diewert and Lawrence (1999) claimed that individual allocative efficiency is a necessary condition for technical efficiency at a group level. The argument is as follows: If a firm is not achieving allocative efficiency, which implies that it has not adequately chosen the optimum input-output mix, then resources could be reallocated to increase the production of at least one output by the group of firms without lowering the production of other outputs while still utilising the same total amounts of all inputs. Quoting Diewert and Lawrence (1999), "the lack of allocative efficiency at the level of the individual firm shows up as the technical inefficiency of a group of firms" (p 162).

It is well known that methods of production improve over time. These improvements create an additional source of productivity change referred to as technical progress[8].

Technical progress - the result of improvements in the design or quality of capital goods or intermediate inputs, discovery of new resources, new methods of doing things, better management and organisational change (e.g., better seeds, new design of milking machines, cows with better genetic merits, new crop rotations). It may be represented by an upward change (shift) in the "best-practice" production frontier (function) (Green, 1997; Griliches, 2001 and OECD, 2001).

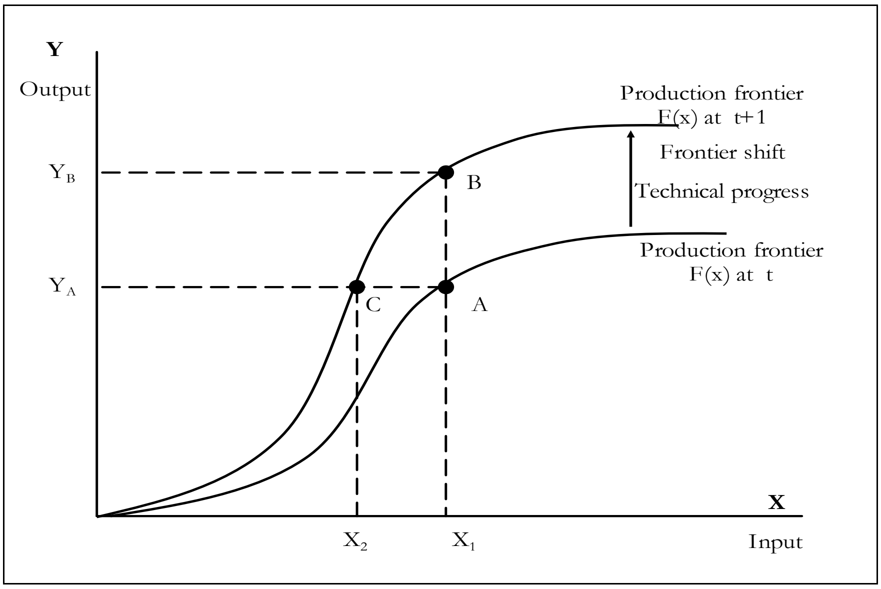
An example in the present case is development of the rotary milking machine or the introduction of a new variety of grass that increases pasture availability. In a graphical representation, it would appear as an outward shift of the production frontier from F(x) at time "t" to F(x) at time "t+1" (Figure 4.2). At time "t" a firm at point A (assuming perfect efficiency for simplicity of exposition) is producing output Y_A inputs X_1. At time "t+1" the same firm would be able to operate at point B or C. At point B the firm increases output quantity to Y_B while maintaining input use at X_1. Alternatively, it can operate at point C by reducing input use to X_2 and keeping output quantity constant at Y_A.

It can be seen that following the shift of the production frontier, the slope of the rays through points B and C are higher than that at point A, hence the firm increases its

[8] In the literature technical and technological change or technical (technological) progress are used interchangeably.

productivity. It can also be seen that point B is superior to point C by exploiting the scale economies.

Figure 4.2 - To illustrate productivity gains through technical progress



Source: Coelli, Rao and Battese (1998)

To summarise, a firm can improve its TFP from one period to another in different ways: by improving its technical efficiency (called technical efficiency change or change in technical efficiency), by exploiting scale economies, due to the effect of technical progress or some combination of these factors.

Nishimizu and Page (1982) first addressed the need for a distinction between technological progress and the changes in the efficiency with which a known technology is applied. They emphasized that this distinction is particularly relevant because "given a level of technology, explicit resource allocation may be required to reach the best-practice level of technical efficiency over time" (p 921). They estimated a parametric (translog) production frontier using linear programming methods and obtained TFP change as "the rate of technical progress plus the rate of change in technical efficiency" (p 928). Färe, Grosskopf, Norris and Zhang (1994) decomposed productivity (TFP) change into technical progress and technical efficiency change but used a non-parametric programming method to compute Malmquist index of TFPG defined by Caves, Christensen and Diewert (1992). Both papers successfully attempted the decomposition of productivity change into two mutually exclusive and exhaustive components, namely, technical progress (TP) and changes in technical efficiency (TE).

Therefore, productivity change for a group of firms encompasses (Färe, Grosskopf, Norris and Zhang, 1994 and Nishimizu and Page, 1982):

Technical progress - the upward shift in the "best-practice" production function (the production frontier).

Technical efficiency change - the movements towards the "best-practice" frontier, which occurred as a result of either learning-by-doing (leading to the mastery of the technology), adoption of innovations, education or imitation.

4.3 A review of the approaches to estimate efficiency and productivity

4.3.1 Technical efficiency

Given that technical efficiency is defined as the departure of the level of production from the maximum attainable output, measurement of inefficiency necessitates estimation of the production frontier. As Green (1997) asserted, gauging the efficiency of individual firms with respect to the "theoretical ideal" is the reason behind frontier estimation.

The two primary methods of frontier estimation are stochastic frontiers and DEA (Coelli, 1995 and Coelli, Rao and Battese, 1998). Both methods involve estimation of "best-practice" frontiers, with the efficiency of a specific decision-making unit being measured relative to the frontier (Green, 1997).

Stochastic frontiers require the specification of a functional form for the production frontier and some distributional assumption regarding the error terms (Coelli, 1995). Estimation is done by maximum likelihood method (ML). The term "stochastic" is motivated by the idea that failure to obtain maximum output might be associated with random disturbances not under the control of the firm (Battese, 1992; Bauer, 1990 and Coelli, 1995; Greene, 1993, 1997 for a review).

DEA is a mathematical programming technique to construct a piecewise linear convex hull of the data. By enveloping the data set, a "best-practice frontier" is obtained. Inefficiency is then computed as the distance of the firm from the "best practice" (lumps noise and inefficiency together; it is therefore deterministic) (Ali and Seiford, 1993; Coelli, 1995; Førsund and Sarafoglou, 2002 and Seiford and Thrall, 1990 for a review).

Both approaches aim to envelope the data in different ways. The essential differences between the two methods can be summarised as follows:

a) The stochastic approach is parametric as it relies on the specification of a functional form to the production frontier. The programming approach is non-parametric.

b) DEA is less demanding than parametric frontiers even when the number of linear programming problems to be solved can be quite large.

c) The parametric frontier approach is subject to specification error by the selection of the functional form, which can be avoided by selecting a flexible functional form at the cost of increasing multicollinearity. The specification error of DEA is minimal.

d) The stochastic approach has a composed error term with a stochastic component (to account for random errors not under the control of the firm) and a deterministic component (that captures departures from maximum output, i.e., inefficiency). In the deterministic model (like DEA), deviations from the frontier (theoretical maximum) are attributed solely to inefficiency, i.e., lumps noise and inefficiency together.

e) The stochastic approach allows for traditional hypothesis testing.

Traditional panel data methods, like fixed effects or random effects, can be used to gauge inefficiency when panel data are available (Ahmad and Bravo-Ureta, 1995). Unlike stochastic frontiers, which rely heavily on assumptions about the error term to be able to separate inefficiency from noise, no assumptions about the distribution of the disturbance term (inefficiency) are required (Green, 1993, 1997). Further the fixed effect method allows for the correlation between inefficiency and the regressors, whereas the maximum likelihood method (ML) (used to estimate stochastic frontiers) explicitly assumes independence between both (Green, 1993, 1997 for a discussion; applications of these methods can be found in Ahmad and Bravo-Ureta, 1995, 1996 and Hallam and Machado, 1996).

When panel data are available, some of the shortcomings of stochastic frontiers are overcome. First, the degrees of freedom for the estimation of the parameters increase. Second, there is no need to assume a specific distribution for the inefficiency term, and third, technical progress and changes in technical efficiency can be investigated simultaneously (Battese, 1992; Coelli, 1995 and Coelli, Rao and Battese, 1998). This later advantage leads on to productivity measurement using efficiency measurement methods.

4.3.2 Productivity growth

In the present study, the Malmquist TFP index will be used to estimate TFPG. Formally, the Malmquist index of TFPG, introduced by Caves, Christensen and Diewert (1992), is defined using distance functions[9]. Later, Färe, Grosskopf, Norris and Zhang (1994) exploited the relationship between the distance functions and Farrell's (1957) technical efficiency measures. They showed that the index breaks down changes in productivity into technical efficiency change and technical progress. This approach has the advantage that it is not biased in the presence of inefficiency. Furthermore, the decomposition into efficiency change and technical progress provides insights into the sources of productivity change (Färe, Grosskopf, Norris and Zhang, 1994 and Nishimizu and Page, 1982). This in turn has important policy implications, given that the two sources of productivity are driven by different factors (Nishimizu and Page, 1982).

The Malmquist index measures productivity change of a firm between two periods by calculating the distances relative to a common technology. An output distance function is considered here. It measures the maximal proportional expansion of the output vector, given an input vector (Coelli, Rao and Battese, 1998).

Färe, Grosskopf, Norris and Zhang (1994) factorized the Malmquist index into technical efficiency change (i.e., the change in the distance of the observed production from the

[9] A review of distance functions is beyond the scope of this thesis. Interested readers are referred to Coelli, Rao and Battese (1998), Coelli and Perelman (1999) and Grosskopf (1993).

current maximum feasible production between years "s" (the base period) and "t") and technical progress (the geometric mean of the shift in technology between the two periods evaluated at input use x_s and x_t) (Figure 4.3).

Hence four distances are required, as follows:

i) the distance between observed output and maximum feasible output at input use x_s and available technology at period "s" (inefficiency at base period)

ii) the distance between observed output in period "s" (at input use x_s and available technology at period "s") and maximum feasible output at input use x_s and available technology at period "t"

iii) the distance between observed output and maximum feasible output at input use x_t in period "t" and available technology at period "t" (inefficiency at next period)

iv) the distance between observed output in period "t" (at input use x_t and available technology at period "t") and maximum feasible output at input use x_t and available technology at period "s"

A graphical example will help to clarify these points. For simplicity of exposition, let us consider a constant return to scale technology with one output and one input (Figure 4.3). The firm is operating inefficiently in periods "s" (the base period) and "t."

At period "s," the firm is operating at point A producing output quantity y_s with inputs at x_s. Maximum output with the prevalent technology at that period is at y_a. Technical inefficiency is equal to the ratio y_s/y_a, which is equivalent to the distance between point A and the frontier (the maximum expansion of output given the input use x_s). That is the above point i).

Similarly, at point B the firm's technical inefficiency is equal to the ratio y_t/y_c, equivalent to the distance between point B and the frontier (the maximum expansion of output given the input use x_t). This in turn is the above-mentioned point iii).

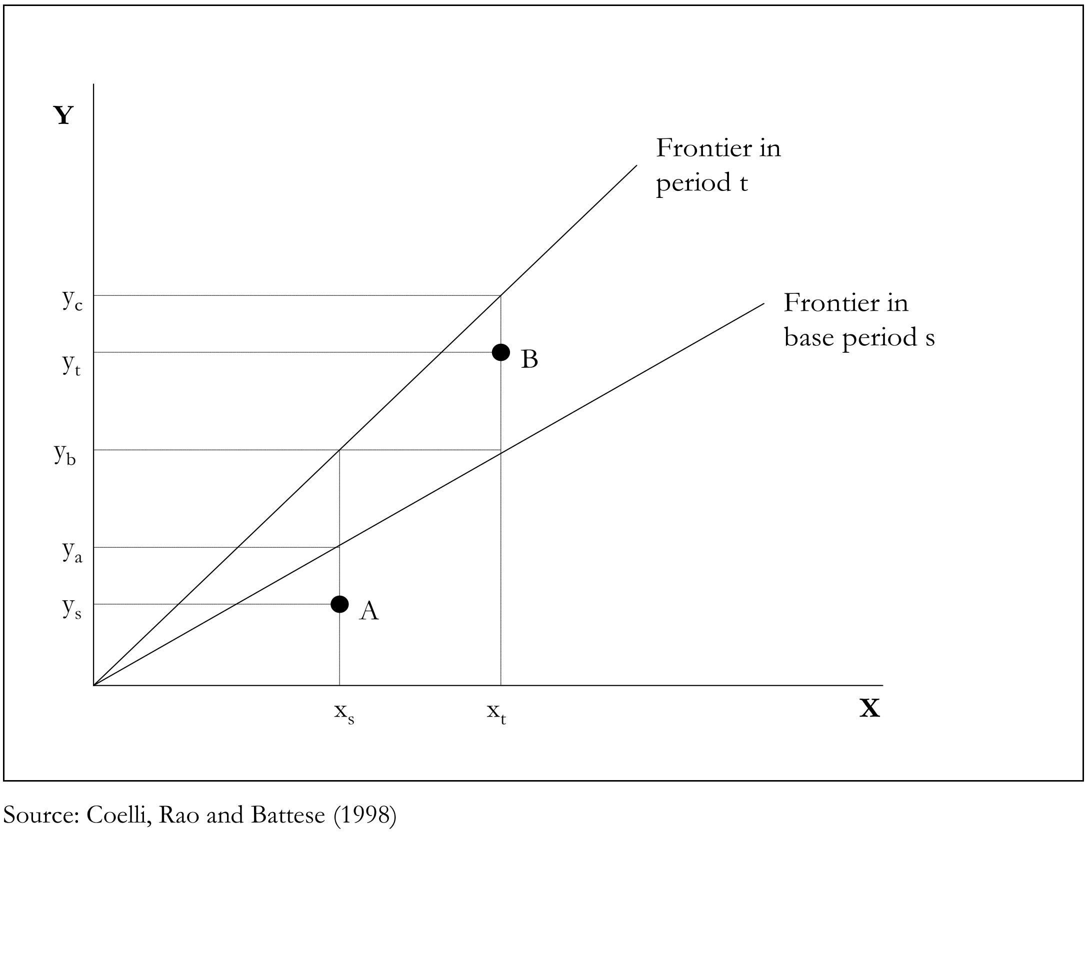
Efficiency change between both periods is equal to the ratio of technical inefficiency at both periods:

$$EC = \frac{y_t / y_c}{y_s / y_a} \qquad (1)$$

The above-mentioned point ii) states: the distance between observed output in period "s" (at input use x_s and available technology at period "s"), i.e., y_s and maximum feasible output at input use x_s and available technology at period "t," i.e., y_b. Hence the distance is defined as y_s/y_b.

Point vi) is as follows: the distance between observed output in period "t" (at input use x_t and available technology at period "t"), i.e., y_t and maximum feasible output at input use x_t and available technology at period "s," i.e., y_b. Hence the distance is defined as y_t/y_b.

Figure 4.3 - Malmquist productivity indices



Source: Coelli, Rao and Battese (1998)

Finally, technical progress is defined as

$$TP = \left[\frac{y_t / y_b}{y_t / y_c} \times \frac{y_s / y_a}{y_s / y_b} \right]^{0.5} \qquad (2)$$

The Malmquist (output-orientated) TFP change index between periods "s" and "t" is then:

$$M(y_s, x_s, y_t, x_t) = EC \times TP = \frac{y_t / y_c}{y_s / y_a} \left[\frac{y_t / y_b}{y_t / y_c} \times \frac{y_s / y_a}{y_s / y_b} \right]^{0.5} \qquad (3)$$

Using the standard distance functions notation the Malmquist index is expressed as follows (Coelli, Rao and Battese, 1998):

$$M(y_s, x_s, y_t, x_t) = \frac{d_o^t(y_t, x_t)}{d_o^s(y_s, x_s)} \left[\frac{d_o^s(y_t, x_t)}{d_o^t(y_t, x_t)} \times \frac{d_o^s(y_s, x_s)}{d_o^t(y_s, x_s)} \right]^{0.5} \qquad (4)$$

A value of M(.) greater than one indicates positive TFPG from period "s" to period "t," while a value less than one indicates TFP decline.

Stochastic frontier and DEA (the method used by Färe, Grosskopf, Norris and Zhang, 1994) can be used to compute the distance functions required to estimate the Malmquist TFP index (Coelli, Rao and Battese, 1998). Herein, the stochastic frontier approach will be used to gauge the MPI. It is easy to debate the relative merits of this way, including the grounding in economic theory, the flexibility of translog from, less sensitive to extreme observations and measurement error or other statistical noise in the data due to modelled distributions of errors and efficiency (Coelli, Rao and Battese, 1998). For the case of agricultural, where the data are heavily influenced by measurement error, SFA is likely to be more appropriate than DEA.

4.4 Methodology

4.4.1 Stochastic frontier analysis with panel data

Stochastic frontier model estimation with panel data has three main advantages. First, estimation of the parameters can be done with a larger number of degrees of freedom. Second, there is no need to assume a specific distribution for the inefficiency term and third, it permits the estimation of technical change and efficiency change simultaneously (Battese, 1992; Coelli, 1995 and Coelli, Rao and Battese, 1998).

The time-varying model for the technical inefficiency effects in the stochastic frontier production function proposed by Battese and Coelli (1992) is considered. The model is defined by:

$$\ln(y_{it}) = f(x_{it}, \beta) + v_{it} - u_{it} \qquad (5)$$

$$u_{it} = \{\exp[-\eta(t-T)]\}u_i \qquad (6)$$

i=1,..., N number of firms

t=1,…, T time period

where:

y_{it} is the output of the i-th firm, at the t-th time;

x_{it} is a (1×k) vector of (transformations of the) input quantities of the i-th firm, at the t-th time;

β is a (k×1) vector of unknown parameters to be estimated;

The u_{it}'s and v_{it}'s jointly comprise the error term.

The v_{it}'s are random errors that are assumed to be identically and independently distributed and have N $(0,\sigma_V^2)$ – distribution, v_{it}'s are independently distributed from the u_{it}'s.

The u_{it}'s represents technical inefficiency effects, and the u_i's are assumed to be i.i.d. non-negative truncations of the N (μ,σ^2)-distribution;

η is an unknown scalar parameter to be estimated

Given the specification of equation (6), if t=T (last period of the panel), then exp[-η(t-T)] equals one and hence $u_{it} = u_i$. So the random variable, u_i, can be considered the technical inefficiency effect of the i-th firm in the last period of the panel. The values of the technical inefficiency effects in the previous periods depend on the scalar η and the number of periods.

Furthermore, the time-varying inefficiency model proposed by equation (6) imposes a rigid parameterisation in that technical inefficiency effects of the different firms at any given time period, *t*, are equal to the same exponential function of the last period inefficiency. Hence the ordering of the firms according to the technical inefficiency is going to be the same across all time periods of the panel. Given the exponential specification, technical efficiency increases at decreasing rates (for $\eta>0$) or decreases at an increasing rate (for $\eta<0$).

A special case of particular interest arises when $\eta=0$ as the time-invariant model for the technical inefficiency effects is defined. Testing the null hypothesis of time-invariant inefficiency is important given the policy implications, and particularly because of the interest of the present study in decomposing TFPG into changes in technical progress and technical efficiency change. If we are in the presence of a time-invariant inefficiency model, then technical efficiency change would be zero.

Finally, another hypothesis of interest given the general frontier model is H_0: $\eta=\mu=0$. This defines a frontier with time-invariant inefficiency effects with half-normal distribution ($u_{it} = u_i \sim N(0,\sigma^2)$).

The simultaneous estimation of the unknown parameters of the stochastic frontier with time-varying inefficiency effects will be done by the method of maximum likelihood implemented in the computer program FRONTIER, Version 4.1 (Coelli, 1994), which estimates the variance parameters in terms of the parameterisation

$\gamma = \sigma^2/\sigma_s^2$, where $\sigma_s^2 = \sigma^2 + \sigma_v^2$, so that γ is bounded between zero and one.

If the value of γ equals zero, the difference between farmer's yield and the efficient yield is entirely due to statistical noise, i.e., there is no inefficiency error so the model is equivalent to the traditional average response function. On the other hand, a value of γ not significantly different from unity implies that the majority of the residual variation is due to the inefficiency effect, i.e., the stochastic term is approximately zero. Therefore, the stochastic frontier model is not significantly different from the deterministic frontier model.

The null hypotheses are tested using the generalised likelihood-ratio test

$$LR = \lambda = -2\{\ln[L(H_0)] - \ln[L(H_A)]\} \qquad (7)$$

where $\ln[L(H_0)]$ and $\ln[L(H_A)]$ are the values of the likelihood function under the null and alternative hypothesis. If the null hypothesis is true, the generalised likelihood-ratio statistic has a chi-square distribution, with the degrees of freedom equal to the number of restrictions. For null hypothesis of no technical inefficiency effects ($\gamma = 0$), critical values derived by Kodde and Palm (1986) from a mixed chi-squared distribution are used.

4.4.2 Estimation of the Malmquist TFP index with stochastic frontiers

As was mentioned above, the stochastic frontier will be used to estimate distance functions needed to obtain the Malmquist TFP index.

Given the specification in (5) and (6) technical efficiency (TE) of the *i*-th farm at the *t*-th year is predicted by

$$TE_{it} = \exp[(-u_{it}) \mid (v_{it} - u_{it})] = \exp(-u_{it}) \qquad (8)$$

Technical efficiency change between two adjacent periods, *s* and *t*, is directly calculated as:

$$TEC_{it} = TE_{it} / TE_{is} \qquad (9)$$

An index of technical progress (TP) between the two periods *s* and *t* can be directly calculated for each farm from the estimated parameters of the stochastic production frontier by evaluating the partial derivative of the production function with respect to time (at a particular data point).

If TP is non-neutral, the index may vary with different input vectors. Hence, following Coelli, Rao and Battese (1998), a geometric mean should be used to estimate the TP index between the adjacent periods. The TP index is calculated as:

$$TP_{it} = \left[\left(1 + (\frac{\partial f(x_{is}, s, \beta)}{\partial s} \right) \times \left(1 + \frac{\partial f(x_{it}, t, \beta)}{\partial t} \right) \right]^{0.5} \qquad (10)$$

The indices of TEC and TP obtained by using equations (9) and (10) respectively can be multiplied to obtain the Malmquist Total Factor Productivity Index:

$$\mathrm{TFP}_{it} = \mathrm{TEC}_{it} * \mathrm{TP}_{it} \quad (11)$$

To summarise, TP measures the shift of the production frontier; TP indicates how far a sample farm lags behind the best practice as represented by the production frontier; and, on the other hand, TEC can be interpreted as how fast a farm catches up with the best practice. Both components are mutually excludible and exhaustive.

4.5 The model specification

The stochastic frontier production function selected to represent the production technology of NZ dairy farms is of a translog form. The translog is a relatively flexible production functions, vis-à-vis the more traditional Cobb-Douglas, and adopting it minimizes the risk of errors in model specification.

The frontier model is defined as follows:

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{5} \beta_j x_{jit} + \sum_{j\leq}^{5} \sum_{k=1}^{5} \beta_{jk} x_{jit} x_{kit} + DR + DPch + V_{it} - U_{it} \quad (12)$$

where the subscripts i and t represent the i-th farmers and t-th year of observation respectively.

In the extensive from:

$$\begin{aligned}\ln Y_{it} &= \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_t t + \beta_{tt} t^2 + \beta_{1t} x_1 t + \beta_{2t} x_2 t \\ &+ \beta_{3t} x_3 t + \beta_{4t} x_4 t + \beta_{11} x_1 x_1 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{14} x_1 x_4 + \beta_{22} x_2 x_2 \\ &+ \beta_{23} x_2 x_3 + \beta_{24} x_2 x_4 + \beta_{33} x_3 x_3 + \beta_{34} x_3 x_4 + \beta_{44} x_4 x_4 + DR + DPch \\ &+ V_{it} - U_{it}\end{aligned} \tag{13}$$

where:

Y denotes output

x_1 to x_4 represent the natural log of the factor input. The stochastic frontier model (SFM) was estimated for different combinations of factors inputs (Table 4)

x_5 is the year of observation, where x_5= 1 to 9 for the seasons 1996/97, 1997/98, 1998/99, 1999/2000, 2000/01, 2001/02, 2002/03, 2003/04 and 2004/05 respectively

DR is a dummy variable equal to 0 if the farm is in Waikato-Taranaki, and equal to 1 if the farm is located in the region conformed by Canterbury-Southland

DPch is a dummy variable equal to 0 for season 1996/97 to season 2000/01 and equal to 1 from then onwards

V_{it} and U_{it} are the random variables defined above

The inclusion of time in the manner depicted in the stochastic frontier model (13) accounts for non-neutral technical change, as it includes terms involving the interaction of the factor inputs and time. Non-neutral or biased technical change implies that the movement of the function will be biased in favour of certain factor input(s) and against others. The existence and nature of technical change is examined using the generalised likelihood-ratio test (LR). Neutral technical change is present if the coefficients of the interaction between time and the factor inputs are jointly equal to zero, i.e., β_{i5} = 0, i = 1, 2, 3, 4. Similarly, if the coefficients of all variables involving year of observation were zero, i.e., $\beta_5 = \beta_{i5} = 0$, i = 1, 2, 3, 4, 5, then there would be no technical change among dairy farmers.

Furthermore, the Cobb-Douglas functional form is nested into (a special case of) the translog. If all the coefficients of the second-order terms are zero, i.e., $\beta_{jk} = 0$, j ≤ k = 1, 2, 3, 4, 5, then a Cobb-Douglas functional form is defined. Hence, the functional form of the stochastic frontier model, in the present case, is determined by testing the adequacy of the Cobb-Douglas relative to the translog using a likelihood-ratio test.

The regional dummy was included in the pooled model (all farms from both regions) to test whether regional differences exist. If the regional dummy is significantly different from zero, then it may be assumed that both regions are not operating under the same production frontier. Therefore, the estimation of separate frontiers for each region is needed in order to confirm the result advanced by the inclusion of the regional dummy.

The DPch (dummy for policy change; equal to 0 for season 1996/97 to season 2000/01 and equal to 1 from then onwards) was included to capture changes that may have arisen due to the change in the organisational structure of the dairy industry. Given the nature of the binary variable, it may also capture other changes that occurred between both sub-periods, e.g., climate, market conditions (milk payout increased significantly following the merger). However, given that output in the production function was measured in physical units, it may be advanced that the effect of the increase in milk payout would not be significant. Regarding the climatic conditions, both sub-periods had good and bad seasons, but it is impossible to ascertain whether climatic conditions are, on average, even between sub-periods (as defined by the dummy).

The null hypotheses (neutral technical change, no-technical change, and that the Cobb-Douglas or the simplified translog functions are adequate) are tested using the LR test (equation 7), where $\ln[L(H_0)]$ and $\ln[L(H_A)]$ are the values of the likelihood function under the null and alternative hypothesis. If the null hypothesis is true, the generalised likelihood-ratio statistic has a chi-square distribution, with the degrees of freedom equal to the number of restrictions, i.e., 4 in the case of neutral technical change, 6 for no-technical change and 15 degrees of freedom to test whether the Cobb-Douglas function is an adequate representation of the production function.

According to Coelli, Rao and Battese (1998), the Malmquist TFP index is best measured relative to a constant return to scale (CRS) technology. Given that TFP indices obtained through a VRS technology may not properly account for the influence of scale, all models were reestimated using a CRS technology.

Following Coelli, Rao and Battese (1998), the restrictions required to impose CRS upon equation (13) are:

$$
\begin{aligned}
&\beta_1 + \beta_2 + \beta_3 + \beta_4 = 1 \\
&\beta_{11} + \beta_{12} + \beta_{13} + \beta_{14} = 0 \\
&\beta_{12} + \beta_{22} + \beta_{23} + \beta_{24} = 0 \\
&\beta_{13} + \beta_{23} + \beta_{33} + \beta_{34} = 0 \\
&\beta_{14} + \beta_{24} + \beta_{34} + \beta_{44} = 0 \\
&\beta_{1t} + \beta_{2t} + \beta_{3t} + \beta_{4t} = 0
\end{aligned}
\tag{14}
$$

In order to impose the restrictions, output and inputs were normalized by dividing them all by one of the inputs. The first input of each model was used for this purpose. Results are invariant to the choice of input (Coelli, Rao and Battese, 1998).

The maximum likelihood estimates of the parameters of the stochastic frontier model under CRS for each region and input/output set are presented in Appendix 2. For some parameter estimates, the t-values are not reported, as they were calculated using the restrictions on (14).

4.6 The database

4.6.1 Data limitations

Data availability was an important limitation when considering the scope of this thesis. As explained is section 1.7, the overriding interest of this thesis was to evaluate and examine TFPG at the farm level. Therefore, not only farm-level data were required. Most importantly, to examine the gains in TFP, data on the same group of farms over a number of years were required. Two sources of microdata on dairy farming were available: Dexcel and Ministry of Agriculture and Forestry (MAF). The Dexcel database gathers a vast amount of information on a large number of farms in different regions over a number of years. However, only a handful of farms are repeated over the years, making this database unsuitable for studies in productivity growth (at least at the farm level). The MAF database, in turn, requests less information from a limited number of farmers, often the same farms over the years. Given that the dairy industry was interested in productivity gains at the farm level, the analysis was performed on the panel data (longitudinal data) gathered in the MAF database.

The Dexcel database could have been used to ascertain whether farms in any one region share the same technology with farms in other regions for any given year. The focus would be on the cross section and the outcome would be a measure of the (in)efficiency with which each farm is applying the technology. Similarly, the robustness of efficiency estimates to variable selection could have been assessed. Furthermore, the vast amount of secondary information on herd characteristics, investment, social factors and weather variables could have been used to examine the determinants of inefficiency. The SFA model proposed by Battese and Coelli (1995) would have allowed examining both, i.e., technological differences between farms in different regions and determinants of inefficiency (more on this in section 10.3).

The database obtained from MAF is used to monitor the production and financial status of farms in terms of their cash income and expenditure. Each year, MAF Policy published a "model" budget for different dairy regions. The "model" is based on the data from a survey of a number of commercial farms for each region[10]. MAF contracts with farm consultants who select the properties based on a range of criteria (e.g., dairy farm within the required region, owner-operator and a commercial unit). The selection is therefore not entirely random, as the consultants tend to pick farms they know. The consultants visit the farms (in mid-May) and collect the financial information for the year ended (or just about to end) and for the new year starting. This is then collated together for the respective regions and provided to MAF. MAF then holds an "industry" meeting within each region that involves a cross section of people involved in the dairy industry (e.g., dairy company, bankers, accountants and some leading farmers) to discuss the information from the survey. The survey is then written up to include a published "model" budget for that region.

MAF Policy supplied farm-level data for the seasons 1996–1997 to 2004–2005 for the present analyses. Two hundred and ten dairy farms were surveyed over the nine year period but the database contained only 861 observations. A balanced (complete) panel would

[10] Phil Journeaux (MAF Policy, Hamilton), personnal communication.

contain a maximum of 1,890 observations (210 farms times 9 years), so the panel is not balanced, i.e., data for some farms on some years are missing. The time length of the MAF database was exploited. Hence, only farms that were surveyed at least in 1997 and 2005 were selected. The number of dairy farms present in both these years totalled 36: 4 in Northland, 8 in Waikato and Taranaki, 9 in Canterbury and 7 in Southland. Data from Northland were discarded because the number of farms was too small to enable the production frontier to be modelled. Therefore, the final panel was comprised of 32 farms. A total of 264 observations remained in the panel, so 24 observations were missing because some farms were not surveyed in all 9 years. Given the number of data in each region, it was decided to pool the four regions into two regions. Region I (RI) includes Waikato and Taranaki, whereas Canterbury and Southland comprises region II (RII). Each region has the same number of farms, 16, with 125 and 139 observations respectively. This aggregation was preferred because it better reflects the commonalities between Waikato and Taranaki—the traditional dairy regions—and the relatively newer dairy regions of Canterbury and Southland (Section 2.6).

The main characteristics of the whole sample are outlined below (Table 4.1, Table 4.2 and Table 4.3). Expenditures were converted into quantities by dividing by annual dairy farm expenses price index (1992/93=1000). Statistics New Zealand provides dairy farm expenses price index on a quarterly basis (Stats NZ). In order to match farm-level data, reported from June to May, the average of the period 2nd quarter 1992–1st quarter 1993 was used as the base year to convert expenditures into 1992/1993 NZ dollars. It was assumed that all farms paid the same prices for each item in any given period. If some farms paid higher prices for a quality input, dividing by the same price converts these inputs into a quality-adjusted input. The deflated expenditures were aggregated into different inputs.

Table 4.1 - Characteristics of the whole sample (average values per farm)

1997-2005	Average	Std Dev	Max	Min
	All farms (264 observations)			
Milk Production (total milksolids, kg)	140,509	114,062	725,000	30,000
Factor inputs				
Cows in Milk (number)	385	273	1,600	104
Area (milking platform, ha)	143	102	555	33
Labour (total hrs per year)	5,044	3,195	22,180	2,250
Feed (all purchased feed, NZ$ 92/93)	69	80	666	6
Fertilizer (expenditure, NZ$ 92/93)	55	55	344	2
Intermediate inputs (health, breeding, shed, feed and fertilizer expenses)	158	152	1,075	21
K2 (depreciation and interest on buildings and machinery and expenditure on repairs and maintenance, NZ$ 92/93)	76	65	470	17
K9 (expenditure on: repairs and maintenance on buildings and machinery, fuel, electricity, rates and insurance, administration and miscellaneous, NZ$ 92/93)	76	61	423	19

Table 4.2 - Characteristics of the sample by region; average values per farm in Region I (Waikato-Taranaki)

1997-2005	Average	Std Dev	Max	Min
	Waikato-Taranaki (125 observations)			
Milk Production (total milksolids, kg)	64,704	24,364	132,000	30,000
Factor inputs				
Cows in Milk (number)	202	62	372	104
Area (milking platform, ha)	67	23	153	33
Labour (total hrs per year)	3,143	784	4,897	2,250
Feed (all purchased feed, NZ$ 92/93)	28	18	98	6
Fertilizer (expenditure, NZ$ 92/93)	23	11	55	2
Intermediate inputs (health, breeding, shed, feed and fertilizer expenses)	67	31	191	21
K2 (depreciation and interest on buildings and machinery and expenditure on repairs and maintenance, NZ$ 92/93)	40	16	92	17
K9 (expenditure on: repairs and maintenance on buildings and machinery, fuel, electricity, rates and insurance, administration and miscellaneous, NZ$ 92/93)	40	13	82	19

Table 4.3 - Characteristics of the sample by region; average values per farm in Region II (Canterbury-Southland)

1997-2005	Average	Std Dev	Max	Min
	Canterbury -Southland (139 observations)			
Milk Production (total milksolids, kg)	208,680	119,897	725,000	52,000
Factor inputs				
Cows in Milk (number)	549	284	1,600	158
Area (milking platform, ha)	212	98	555	49
Labour (total hrs per year)	6,753	3,561	22,180	2,266
Feed (all purchased feed, NZ$ 92/93)	106	95	666	12
Fertilizer (expenditure, NZ$ 92/93)	84	62	344	13
Intermediate inputs (health, breeding, shed, feed and fertilizer expenses)	240	170	1,075	48
K2 (depreciation and interest on buildings and machinery and expenditure on repairs and maintenance, NZ$ 92/93)	108	75	470	24
K9 (expenditure on: repairs and maintenance on buildings and machinery, fuel, electricity, rates and insurance, administration and miscellaneous, NZ$ 92/93)	107	70	423	33

4.6.2 Impact of data limitations

The number of observations, 125 for Waikato-Taranaki and 139 for Canterbury-Southland, is not representative of the population. Over the period of the analysis, there were more than 6,000 farms in Waikato-Taranaki and more than 1,200 farms in Canterbury-Southland (LIC). This issue imposes a restriction on the generalisation of the outcome of the analysis to their respective region. However, it does not invalidate the results themselves, as other studies applied SFA to estimate efficiency and productivity with a similar number of observations.

Battese and Coelli (1992) proposed the time-varying model for the technical inefficiency effects in the stochastic frontier production function for panel data with a similar number of observations. Other studies focused on dairy farm productivity using a parametric approach were performed using a similar number of observations (Table 4.4). Studies using deterministic frontier models include the work by Alvarez and Gonzales (1999), Arias and Alvarez (1993), Hallam and Machado (1996), Maietta (2000), Piesse, Thirtle and Jurk (1996), and Turk (1995). Applications of stochastic production frontiers to dairy using panel data include the papers by Ahmad and Bravo-Ureta (1995 and 1996), Bailey et al.

(1989), Battese and Coelli (1988), Cuesta (2000), Heshmati and Kumbhakar (1994), Kumbhakar and Hjalmarsson (1993), Kumbhakar and Heshmati (1995), and Reinhard, Knox and Thijssen (1999). The number of observations ranges from 43 (Battese, 1988) to 1,545 (Reinhard, 1999). Five of the studies mentioned used a lower number of observations than the present study (Ahmad, 1995; Arias and Alvarez, 1993; Bailey, 1989; Battese, 1988 and Hallam and Machado, 1996).

Table 4.4 - Overview of empirical parametric studies on productivity and efficiency in dairy farms with panel data

First Author	Year of Publication	Country	No. Observations	Average Technical Efficiency
Deterministic Frontier				
Alvarez, A.	1999	Spain	410	72.0
Arias, C.	1993	Spain	112	73.0
Hallam, D.	1996	Portugal	85	57.0
Maietta, W.	2000	Italy	533	55.0
Piesse, J.	1996	Slovenia	204	53.0
Turk, J.	1995	Slovenia	272	77.1
Stochastic Frontier				
Ahmad, M.	1995	USA	96	77.0
Ahmad, M.	1996	USA	1,072	85.9
Bailey, D.	1989	Ecuador	68	78.1
Battese, G.	1988	Australia	43	70.1
Cuesta, R.	2000	Spain	410	77.6
Heshmati, A.	1994	Sweden	600	81.2
Kumbhakar, S.	1993	Sweden	232	86.2
Kumbhakar, S.	1995	Sweden	1,425	83.1
Reinhard, S.	1999	Netherlands	1,545	89.4

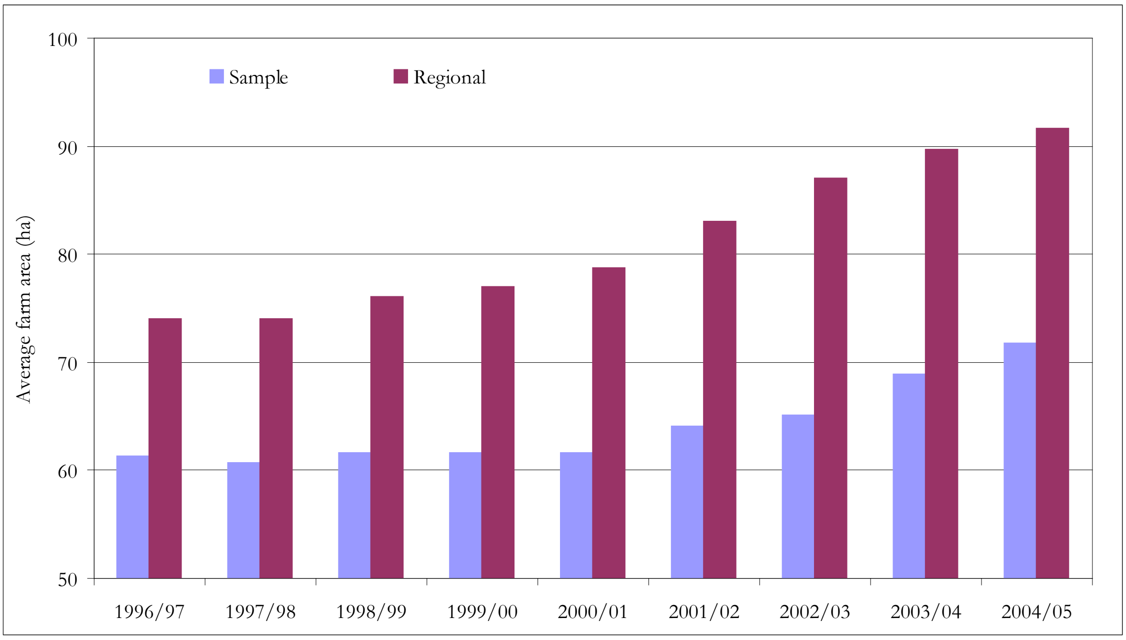
Another issue of concern are the differences in average farm size between the sample and the population. The bias in average size of the farms (measured either in area or number of cows) of the sampled farms with respect to the population imposes a restriction to the generalisation of results to the region. Average farm size, measured by area of farm and number of cows, for sampled farms in Waikato-Taranaki was smaller than the regional average estimated using LIC database[11] (Figure 4.5 and Figure 4.6). Conversely, average

[11] Livestock Improvement Corporation "Dairy Statistics" various issues.

farm size for sampled farms in Canterbury-Southland was higher than the regional average (Figure 4.7 and Figure 4.8). Furthermore, size differences tend to increase over the period for both regions.

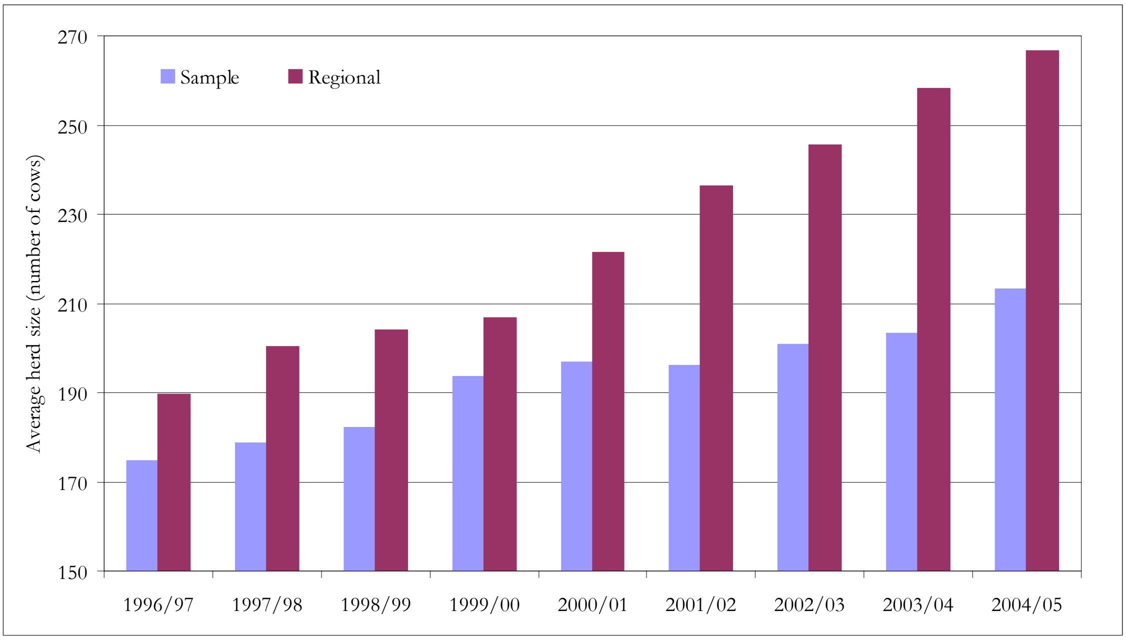
Average farm size, measured by area of farm and number of cows, for sampled farms in Waikato-Taranaki is smaller than the regional average estimated using LIC database[12] (Figure 4.4 and Figure 4.5). Average size differences increased over the period. Meanwhile, difference in average farm size expanded from 13 ha to 22 ha and difference in average herd size, augmented to 50 cows at the end of the period from 15 cows at the beginning of the period.

Figure 4.5 - Average farm area for the sample farms and the region for Waikato-Taranaki



[12] Livestock Improvement Corporation "Dairy Statistics" various issues.

Figure 4.6 - Average herd size for the sample farms and the region for Waikato-Taranaki



Conversely, average farm size for sampled farms in Canterbury-Southland was higher than the regional average. Difference in average farm size increased from 30 ha to 45 ha. Similarly, average herd size rose from 45 cows to 78 cows.

Figure 4.7 - Average farm area for the sample farms and the region for Canterbury-Southland

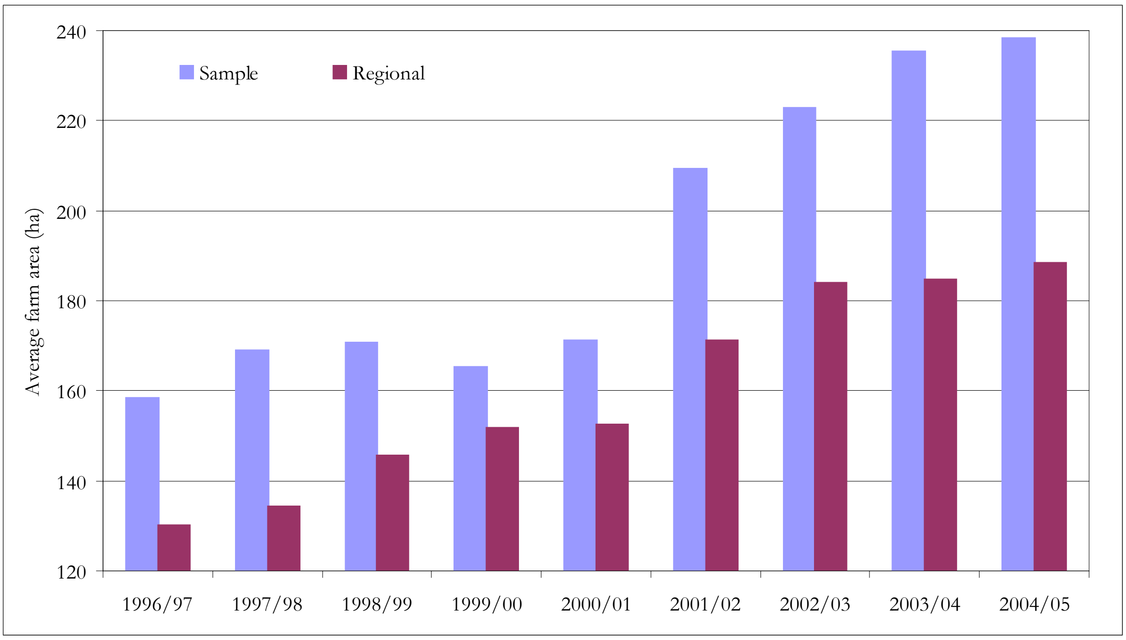
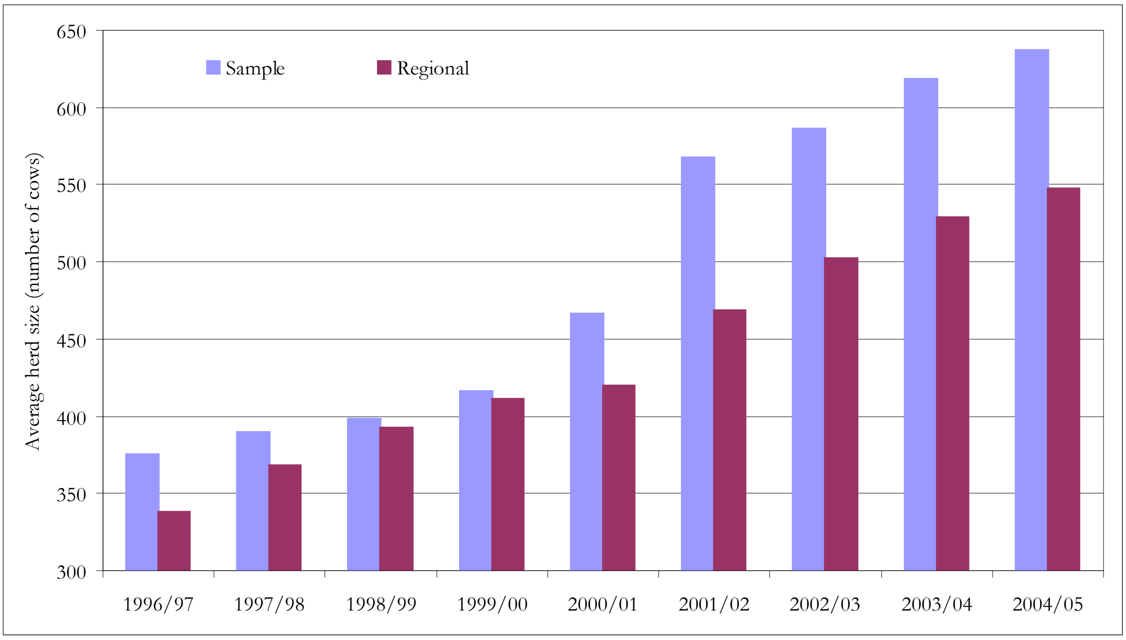


Figure 4.8 - Average herd size for the sample farms and the region for Canterbury-Southland



As mentioned above, the number of farms in the sample is not representative of the number of farms in the population for either of the two regions. Differences in average size between the sample and the population are by defect for Waikato-Taranaki (Figure 4.4 and Figure 4.5) and by excess for Canterbury-Southland (Figure 4.6 and Figure 4.7). Therefore, TFP estimates should be taken with care, as they may not reflect the true situation in both regions. Average efficiency of the sample may be biased with respect to average efficiency of the region. Hallam and Machado (1996) and Kumbhakar, Ghosh and McGuckin (1991) reported that larger farms tend to be more efficient. Weersink, Turvey and Godah (1990) found that the level efficiency is positively associated with size but at a decreasing rate. Therefore, if results reported here are generalised to the region, they may understate average efficiency score for Waikato-Taranaki and overstate efficiency score for Canterbury-Southland. It is difficult to ascertain the impact of the bias in TFPG estimates. The author is not aware of any study that tested the dynamic relation between size increases and TFPG.

Data in this field are always inadequate and incomplete, but this fact is not a sufficient reason for ignoring them or for proceeding to use an unsatisfactory model simply because good data are available for it and are not for a more powerful model. One of the important attributes of good analysis is the effectiveness with which available data are used in the context of the most suitable model. An important task, then, is to use the data that are available in an effective model to see what they show. One must then be equipped to appraise the results in terms of whether they are significantly affected by the shortcomings of the data. This is a much more useful approach than that of using less powerful models (or no formal models) with better data. In the latter approach, the analyst will then have to try to decide the extent to which the results are defective due to the model or what the data mean when they are presented with no model to guide interpretation.

4.7 Selection of input variables

Milk production was selected as the output variable. Gross farm revenue can be used to aggregate the multiple outputs produced (milk, beef, excess forage sold, equipment hire) by a dairy farm, at the cost of capturing allocative and technical efficiency effects in the inefficiency term (Jaforullah and Devlin, 1996). Furthermore, in order to convert gross farm revenue into a "quantity," it has to be deflated by the Consumer Price Index (CPI). This poses another problem. The milk price index and the CPI moved closely together between seasons 1996/97 to 1999/00. However, milk payout increased by 32% in nominal terms for season 2000/01, remained at the same level for two more seasons, and finally declined to the levels of 1996/97 in 2003/04. Hence, deflating gross farm revenue by CPI would overestimate milk production. Given that the share of milk revenue in total farm revenue was greater than 78% for all farms in any given year, milk production per farm in physical units was preferred as the output variable. Ahmad and Bravo-Ureta (1995, 1996), Bravo-Ureta (1986), Fraser and Cordina (1999), Mbaga et al. (2003), Tauer (1998) and Piesse, Thirtle and Turk (1996) followed a similar approach.

The number of cows in milk and effective farm area were chosen as variables. Output is measured in physical units, i.e., kgs of milksolids. Therefore, only cows in milk (following Ahmad and Bravo-Ureta, 1995, 1996; Bravo-Ureta, 1986 and Kumbhakar, Gosh and McGuckin, 1991) and effective farm area can be considered as inputs in the production process. As was explained in Chapter 2, cow numbers and farm area has increased at faster rates in Canterbury-Southland than in Waikato-Taranaki. Using "cows" and "area" as input variables would allow the different pattern of expansion between regions to be shown. Furthermore, these two inputs are readily accessible.

Labour input is measured as the total yearly hours worked by family and hired labour on the farm. As mentioned above, all the studies reviewed use labour as an input. The discussion, if any, was centred on how was it measured, physical or monetary. The database provides information on total wages but does not include the owners' wages. In order to transform total wages into a physical unit (total hours worked), total wages was divided by the average hourly earnings reported by the Reserve Bank of New Zealand. Furthermore, given that the database precluded identifying farms that were owner-operated, and that most, if not all, owners are somehow involved in farming activities, it was decided to add the hours worked by the owner to all farms in the sample. The owners' hours worked per year was assumed to be 58 hours per week as reported in the Economic Survey of New Zealand Dairy Farmers by Dexcel.

Given the increasing use of feed supplements in NZ dairy farming, "feed expenditure" was considered separately and so was "fertiliser expenditure" to allow more technical details to be modelled (Ahmad and Bravo-Ureta, 1995, 1996). Regrettably, the dataset had no information on the type of supplementary feed purchased. Having this information would have enabled different strategies in feeding practices to be taken into account. For example, given the same feed expenditure for two different farms, the cost of supplementary feed purchased may be different. Therefore effective quantity of supplements purchased may be different, e.g., between all concentrate or all hay. Similarly, the database had no information about the amount of fertilizer used as feed supplement. An aggregate measure of "intermediate inputs" comprised of health, breeding, shed, feed and fertilizer expenditure was created à la Brümmer, Glauben and Thijssen (2002), albeit a slightly different approach to aggregate was taken. Expenditure on each input was deflated by the corresponding price index taken from the Farm Expenses Price Index for Dairy Farms (Statistics New Zealand). Aggregating inputs comes at the cost of sacrificing potentially useful information.

Capital input (K2) was measured as the user cost, defined as the sum of depreciation and interest on the stock of capital (Ahmad and Bravo-Ureta, 1995; Heshmati and Kumbhakar, 1994; Kumbhakar, Biswas and Bailey, 1989; Kumbhakar and Heshmati, 1995 and Kumbhakar and Hjalmarsson, 1993). The database included a stock measure of capital for "land and buildings" and "vehicles and machinery." However, an aggregate measure of capital for "land and buildings" does not allow different rates of depreciation to be applied depending on the intensity at which capital is used. Hence, the value of the "buildings" was set at 12% of the stock value of "land and buildings." Depreciation for "buildings" was set at 4% and for "vehicles and machinery" at 10%. The average interest rate of the government bond for the period, at 7%, as reported by the Reserve Bank of New Zealand, was chosen to proxy the opportunity cost of employing capital elsewhere. Depreciation on "buildings" was deflated by the average price of dairy farm land as estimated by Quotable Value New Zealand (Situation and Outlook for New Zealand Agriculture and Forestry, 2006). "Vehicles and machinery" was deflated by the price index on repairs and maintenance. Meanwhile, interest was corrected by the corresponding price index from the Farm Expenses Price Index for Dairy Farms (Statistics New Zealand).

Farm surveys do not usually include information about the capital stock on land, buildings and machinery. Conversely, expenditure on different items is always reported. Therefore, a different measure of capital input (K9) was estimated. It is comprised of the expenditure on electricity, freight, fuel, rates and insurance, repairs and maintenance on buildings, vehicles and machinery, administration and miscellaneous (à la Ahmad and Bravo-Ureta, 1996), all deflated by the corresponding price index taken from the Farm Expenses Price Index for Dairy Farms (Statistics New Zealand).

As mentioned in Chapter 2, the industrial organisation of the dairy industry changed dramatically in 2001 with the demise of the NZDB and the creation of Fonterra. Therefore, a dummy variable for policy change (DPch) was included to capture the impact of this change on the production frontier, if any.

The models defined had alternative combination of factor inputs, and the same output. Model J7 was defined following Brümmer, Glauben and Thijssen (2002) and Kumbhakar and Hjalmarsson (1993). Model L8 resembles input selection made by Cuesta (2000). The difference is that Cuesta (2000) used "cows" as a proxy of capital, while model L8 includes a measure of "capital." Model Y5 followed Bravo-Ureta and Rieger (1990) and Tauer (1998). Model K9 was a variation of Model L8, where originally effective area was substituted by fertilizer and K2 by K9. The time trend and the dummy for policy change were included in all models (Table 4.9).

Table 4.9 - Models estimated and variables used; X shows the variables that were included in each of the models

Variables	Code	Model			
		J7	L8	Y5	K9
Output (Milk Production)	Y	X	X	X	X
Factor inputs					
Cows in Milk (number)	CW		X		X
Area (milking platform, ha)	A	X	X		
Labour (total hrs per year)	L	X	X	X	X
Feed (all purchased feed, NZ$ 92/93)	FD			X	
Fertilizer (expenditure, NZ$ 92/93)	FT			X	X
Intermediate inputs (health, breeding, shed, feed and fertilizer expenses)	II	X			
Depreciation and interest on: buildings and vehicles and machinery plus expenditure on repairs and maintenance (NZ$ 92/93)	K2	X	X	X	
Expenditure on: repairs and maintenance on buildings and machinery, fuel, electricity, rates and insurance, administration and miscellaneous (NZ$ 92/93)	K9				X
Year	Y	X	X	X	X
Dummy for policy change	DPch	X	X	X	X

Other aggregation of inputs and combinations of variables were tested. Some of them followed studies reviewed before, some not. The four models reported were those economically meaningful. For example, negative labour input elasticity implies excess labour. Common sense indicates that this cannot be the case in NZ dairy farming, where labour shortages are a huge problem. However, it can be logical in Africa for small family-operated dairy farms, where excess labour at home is masking unemployment at a national level. So for the case of NZ, we might expect high labour elasticity.

4.8 Empirical results

For the sake of simplicity, each model will be introduced separately. For each model, the stochastic frontier for the pooled sample will be presented first. Results of regional frontiers will be presented second. All stochastic frontiers are estimated using a variable return to scale (VRS) technology.

Following each model, a series of hypotheses will be tested to determine the preferred functional form and to examine the existence and nature of technical change. Next, elasticities for each factor input will be estimated and average efficiency scores presented. Finally, values for the two regions will be compared. To conclude, regional estimates of TFPG, technological progress and technical efficiency change will be compared across models.

4.9 Concluding comments

This section introduces the approaches to estimate efficiency and productivity using frontier methods. Both SFA and DEA can be used to compute the distance functions required to estimate the MPI (Coelli, Rao and Battese, 1998). The parametric approach (SFA) was pursued rather than the mathematical programming approach (DEA) based on two important reasons. First, the SFA relies on the specification of a functional form for the production frontier and the estimation of parameters is required (Coelli, Rao and Battese, 1998). Therefore, this allows for traditional hypothesis testing, necessary to evaluate differences in technology between regions, which is required to achieve the objectives of the current study and is not available in DEA. Second, SFA has a composed error term with a stochastic component (to account for random errors not under the control of the firm) and a deterministic component (that captures departures from maximum output, i.e., inefficiency) (Battese and Coelli, 1992 and 1995). This would help to attenuate some of the shortcomings posed by the limited number of observations (data were collected for purposes other than the estimation of productivity and the number of observations are small). The number of observations impose a restriction on the transferability of results, however it does not invalidate the results themselves, as other studies applied SFA to estimate efficiency and productivity with a similar number of observations.

As explained in section 1.7, one of the contributions to knowledge of the present thesis is to shed light on the sensitivity of technical efficiency and productivity estimates to the selection of the input/output set, i.e., the characterisation of the technology. All of the studies reviewed (Chapter 3) reported only one input/output combination. Different input/output combinations were proposed following previous studies in dairy farm efficiency and productivity. Those four reported here had outcomes economically meaningful.

CHAPTER 5

5 Results for Model J7

5.1 Determination of the preferred functional form

Model J7 was defined in terms of the following factor inputs: area (hectares), labour (hours worked), capital (K2, depreciation and interest on the stock of building and vehicles and machinery plus expenditure on repairs and maintenance deflated by the corresponding price index) and intermediate inputs (comprised by the aggregation of the expenditure on health, breeding, shed, feed and fertiliser deflated by the corresponding price index). Empirical results were obtained by using the stochastic frontier production model with time-varying inefficiency effects defined in Section 4.7.

5.1.1 All data pooled across both regions

Given the specifications of the stochastic frontier, various hypotheses were tested to determine the preferred functional form and the distribution of the random variables associated with the existence of technical inefficiency and the residual error term (Table 5.1). The coefficient on the dummy introduced to capture the effects of the policy change was not significant ($t<2$). This result was confirmed by the LR test.

The translog stochastic frontier production model was estimated first. The first null hypothesis that the Cobb-Douglas production function was an adequate representation for the NZ dairy data was rejected. Next, the null hypothesis that technical change is Hicks-neutral was accepted. Similarly, the hypothesis of no technical change was also accepted. This refers to no time effects (or exogenous technical change) in the production frontier.

Table 5.1 – Model J7, data for both regions: generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function

Null Hypothesis (*Ho*)	Loglikelihood function (LLF)	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given pooled sample	204.67			
A Cobb-Douglas function is adequate	189.89	29.56	$\chi^2_{.05,\,15} = 25.00$	Reject *Ho*
Technical change is neutral	201.62	6.1	$\chi^2_{.05,\,4} = 9.49$	Accept *Ho*
NO technical change	201.21	6.92	$\chi^2_{.05,\,6} = 12.6$	Accept *Ho*
Traditional average response function is adequate representation of the data (w.r.t. No technical change) ($\gamma=\mu=\eta=0$)	174.58	53.27	$\chi^2_{.05,\,3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant (w.r.t. No technical change) $\mu=\eta=0$	196.95	8.52	$\chi^2_{.05,\,2} = 5.99$	Reject *Ho*
Technical inefficiencies have a half-normal distribution (w.r.t. No technical change) $\mu=0$	201.19	0.04	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*
Technical inefficiencies are time invariant (w.r.t. No technical change) $\eta=0$	196.97	8.48	$\chi^2_{.05,\,1} = 3.84$	Reject *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

Given the specifications of the translog stochastic frontier with no-technical change as preferred functional form, it is evident that the traditional average response function, in which farms are assumed to be fully technically efficient, is not an adequate representation of the data (i.e., the null hypothesis H_0: $\gamma=\mu=\eta=0$ is rejected). Similarly, the null hypotheses that time-invariant models for farm effects apply are also rejected (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$ are rejected), indicating that technical efficiency levels vary significantly over time (Table 5.1). Finally, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was accepted, i.e., the technical inefficiency effects have a N $(0,\sigma^2)$ distribution.

Next, the translog stochastic frontier model with no-technical change was estimated with the regional dummy. The value of the LLF was 204.636. The coefficient of the regional dummy has a value of 0.1097 (*t-value*=2.453) and it was significantly different from zero at 5 %. This result was confirmed by the likelihood-ratio test (eq. 7, Section 4.4.1).

The null hypothesis, that the regional dummy is zero, is the value of the LLF for the stochastic frontier model with no-technical change, i.e., 201.21 (Table 5.1). Meanwhile, the alternative hypothesis has a value of 204.636 (the value of the log-likelihood function for the translog stochastic frontier model with no-technical change and the regional dummy). Hence the LR-test statistic has a value of 6.852 [-2 * (201.21 – 204.636)], which is greater than the critical value defined by the chi-squared distribution with one degree of freedom ($\chi^2_{.05,\,1}$ = 3.84). Therefore, based on this result, there is *a priori* evidence that the stochastic frontier model differs between regions. Further, based on the sign of the dummy, it can be advanced that, given the production function defined by the input/output set, Canterbury-Southland sampled farms are, on average, 10.97% more productive than sampled farms in Waikato-Taranaki, *ceteris paribus*.

5.1.2 The Waikato-Taranaki sample

The value of the log-likelihood function, for the translog stochastic frontier model with time varying inefficiency effects for Waikato-Taranaki, is 128.219. The coefficient of the dummy introduced to capture the effects of the policy change was not significant (t-statistic<2). This result was confirmed by the LR test. Therefore, it may be argued that the policy change[13] has no impact on the production function. However, the dummy for policy change may be also capturing other effects than the policy change itself. Therefore, more research is needed in order to disentangle other effects that may be influencing the results discussed here. Results of the different hypotheses tested are presented below (Table 5.2).

The Cobb-Douglas production frontier is chosen based on the rejection of the translog as inadequate. This implies that the input elasticities are the same between farms. In contrast to the pooled sample, the hypothesis of no technical change was rejected.

Given the specifications of the CD stochastic frontier with Hicks-neutral technical change as preferred functional form, it is evident that the traditional average response function, in which farms are assumed to be fully technical efficient, is not an adequate representation of the data (i.e., the null hypothesis H_0: $\gamma=\mu=\eta=0$ is rejected). Conversely, the null hypotheses that time-invariant models for farm effects apply are accepted (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$ are accepted), indicating that technical efficiency levels do not vary significantly over time (Table 5.2). Finally, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was accepted, i.e., the technical inefficiency effects have a $N(0,\sigma^2)$ distribution.

[13] Refers to the change in the institutional organization of the dairy industry, called for simplicity policy change

Table 5.2 - Data for Waikato-Taranaki: Generalised Likelihood-Ratio Tests of Null Hypotheses for Parameters in the Stochastic Frontier Production Function

Null Hypothesis (*Ho*)	Loglikelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given pooled sample	128.22			
A Cobb-Douglas function is adequate	118.9	18.64	$\chi^2_{.05, 15} = 25.00$	Accept *Ho*
NO technical change	114.209	9.38	$\chi^2_{.05, 1} = 3.84$	Reject *Ho*
Traditional average response function is adequate representation of the data (w.r.t. No technical change) ($\gamma=\mu=\eta=0$)	98.27	41.26	$\chi^2_{.05, 3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant (w.r.t. CD) $\mu=\eta=0$	117.01	3.78	$\chi^2_{.05, 2} = 5.99$	Accept *Ho*
Technical inefficiencies have a half-normal distribution (w.r.t. No technical change) $\mu=0$	117.89	2.02	$\chi^2_{.05, 1} = 3.84$	Accept *Ho*
Technical inefficiencies are time invariant (w.r.t. No technical change) $\eta=0$	117.6	2.6	$\chi^2_{.05, 1} = 3.84$	Accept *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

5.1.3 The Canterbury-Southland sample

Given the specification of the translog stochastic frontier production function with time varying inefficiency effects, for Canterbury-Southland farms, the value of the log-likelihood function is 118.98 (Table 5.3). As for Waikato-Taranaki, given the results of the LR test, the dummy for policy change was not significant. The null hypotheses that the Cobb-Douglas is an adequate representation and that there is no technical change were rejected. However, the hypothesis of Hicks-neutral technical change was accepted (Table 5.3).

Given the specifications of the Hicks-neutral translog stochastic frontier as the preferred functional form, it is evident that the traditional average response function, in which farms are assumed to be fully technical efficient, is not an adequate representation of the data (i.e., the null hypothesis H_0: $\gamma=\mu=\eta=0$ is rejected). Similarly, the null hypotheses that time-invariant models for farm effects apply are also rejected (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$ are rejected), indicating that technical efficiency levels vary significantly over time (Table 5.3). Finally, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was accepted, i.e., the technical inefficiency effects have a $N(0,\sigma^2)$ distribution.

Table 5.3 – Model J7, data for Canterbury-Southland: Generalised Likelihood-Ratio Tests of Null Hypotheses for Parameters in the Stochastic Frontier Production Function

Null Hypothesis (*Ho*)	Loglikelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given pooled sample	118.98			
A Cobb-Douglas function is adequate	96.11	45.74	$\chi^2_{.05,\,15} = 25.00$	Reject *Ho*
Technical change is neutral	114.32	9.32	$\chi^2_{.05,\,4} = 9.49$	Accept *Ho*
No technical change	103.57	30.82	$\chi^2_{.05,\,6} = 12.6$	Reject *Ho*
Traditional average response function is adequate representation of the data (w.r.t. neutral translog) ($\gamma=\mu=\eta=0$)	99.83	28.74	$\chi^2_{.05,\,3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant (w.r.t. neutral translog) $\mu=\eta=0$	102.75	23.14	$\chi^2_{.05,\,2} = 5.99$	Reject *Ho*
Technical inefficiencies have a half-normal distribution (w.r.t. translog) $\mu=0$	114.21	0.22	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*
Technical inefficiencies are time invariant (w.r.t. neutral translog) $\eta=0$	101.53	25.58	$\chi^2_{.05,\,1} = 3.84$	Reject *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

5.1.4 Testing the existence of a common frontier

As was previously mentioned, the value of the coefficient of the regional dummy included in the pooled sample indicates that both regions may not be operating under the same technology. The appropriateness of dividing the sample into two regions is tested by a likelihood-ratio test (Table 5.4) (Battese, Rao, O'Donnell, 2004 and Kumbhakar, Biswas and Bailey, 1989). The null hypothesis of a single production function is the value of the log-likelihood function for the stochastic frontier obtained by pooling the data from both regions (preferred model in Table 5.1). The alternative hypothesis is obtained by adding the values of the log-likelihood functions for both regions (preferred models in Table 5.2 and Table 5.3).

Table 5.4 – Model J7, generalized likelihood-ratio tests of null hypothesis that regions share a common stochastic frontier production function

	Log-likelihood (parameters estimated)	LR-Test Statistic (degrees of freedom)	Critical value (0.05)	Decision
Waikato-Taranaki Cobb-Douglas $\mu=\eta=0$	117.01 (8)			
Canterbury-Southland TL with neutral technical change, $\mu=0$	114.21 (20)			
H_A: ∑ [Log-likelihood (WT)]+ [Log-likelihood (CS)]	231.2 (28)			
Ho: Pooled sample TL with no-technical change, $\mu=0$	201.19 (18)	-2*(201.19-231.2) = **60.02** df. (28-18=10)	$\chi^2_{.05,\,10}$ = **18.3**	Reject *Ho*

The degrees of freedom for the Chi-squared test are the difference between the number of parameters estimated under the alternative and the null hypotheses. Note that the number of parameters estimated for the non-neutral translog is 25: 21 parameters in the frontier function (20+1 for the constant), 2 for the variance terms (sigma and gamma), 1 for the inefficiency effect (u_i) and 1 for the scalar η.

The null hypothesis that both regions share the same underlying technology was rejected, confirming the *a priori* result obtained by using the regional dummy in the pooled stochastic frontier. Therefore, according to the log-likelihood ratio test, farm-level data in the two regions are not generated from a single production frontier and the same underlying technology. Hence, there are good reasons to estimate the stochastic frontier for each region separately to evaluate such differences. This outcome is expected considering the increasing divergence in productivity per cow and productivity per ha between regions in both islands of NZ over the period of study (Figures 2.1 and 2.2). Maximum likelihood parameter estimates for the stochastic production frontier of both regions are presented below.

5.2 Waikato-Taranaki

As was mentioned above (Table 5.2), the preferred functional form for the Waikato-Taranaki region, given the results of the LR test, is a CD form with time invariant technical efficiency and a half-normal distribution. Estimates of the parameters associated with the stochastic frontier are reported below (Table 5.5).

The coefficients on area, labour and intermediate input in the production function are significantly different from zero at 5%. Meanwhile, the coefficients on capital and on the time trend are not significant (Table 5.5). However, the LR test rejects the hypothesis that the coefficient of capital was zero. With respect to the time trend, when the constant return to scale (CRS) model was estimated to evaluate the productivity growth, the coefficient of the time trend was significantly different from zero. Hence, both variables, capital and time, were retained.

The value of maximum likelihood estimate for γ is 0.7966 and is significant at 5%. This test statistic reinforces the notion that technical inefficiency in the Waikato-Taranaki sample is present but also that noise plays a role.

Table 5.5 – Model J7, data for Waikato-Taranaki: maximum likelihood estimates for parameters of the stochastic frontier under VRS (variable returns to scale)

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	5.2206	10.4498 ***
Area (A)	β_1	0.2827	5.3104 ***
Labour (L)	β_2	0.3104	5.4045 ***
Capital (K2)	β_3	0.0383	1.0054
Intermediate input (II)	β_4	0.4052	8.6861 ***
Year (Y)	β_t	0.0047	1.6940
Variance parameters			
Sigma	σ^2	0.0364	2.9192 **
Gamma	Γ	0.7966	9.6539 ***
Technical inefficiency effect	μ_i	Restricted to zero	
Time-varying inefficiency	H	Restricted to zero	
Loglikelihood function		**117.01**	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Given the function form, a Cobb-Douglas, the estimated coefficients are the output elasticities (Table 5.5). These are the same across all farms and over time. Over the period, the major determinant of dairy production growth was intermediate input, with an average output elasticity of 0.40, followed by labour at 0.31, area of farm at 0.28 and capital at 0.04 (Table 5.5). On average for the period, a 1% increase in area of farm results in a growth of 0.28% in milk production *ceteris paribus*. Similarly, the outcome of a 1% increase in capital is an expansion of 0.04% in milk production.

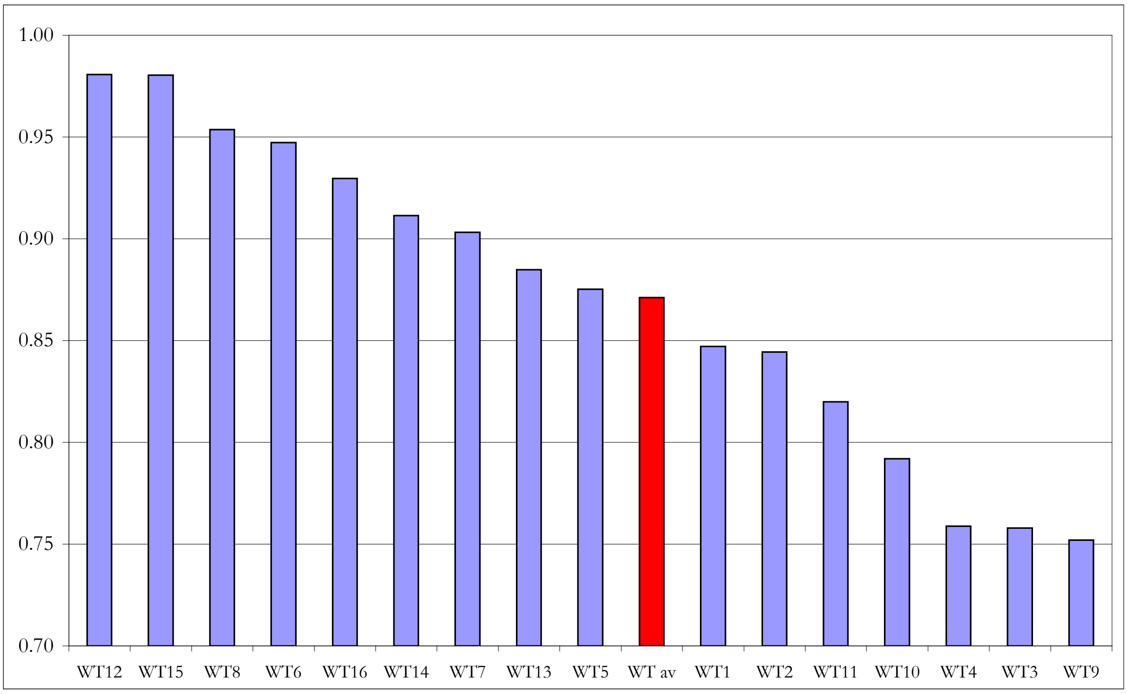
The elasticity of scale is found to be 1.036, indicating increasing returns to scale in dairy farms, implying that a 1% increase in all input would result in a 1.036% increase in output.

The frontier was shifting upwards (the region experienced technical progress) at a constant rate. The rate of exogenous technical progress is found to be increasing productivity by 0.47% per annum.

Given that the estimate of the parameter η is zero, the technical efficiencies were constant over time. The mean overall technical efficiency is 87.1%. This result indicates that the volume of milk produced by the farms in the sample during the period could have been achieved with approximately 13% fewer resources, provided that all farms were technically efficient. For those farms with the lowest efficiency scores (WT4, WT3 and WT9) this implies that, over the period, the volume of milk produced could have been achieved with 20% fewer resources, provided they applied the technology as successfully as farm WT8 (Figure 5.1)

The dispersion in technical efficiencies of dairy farmers is considerable, ranging between 0.75 and 0.98. Furthermore, it can be seen that only two farms ranked high in technical efficiency (more than 95%), while four others have technical efficiencies lower than 80%. Given the small rate of technical progress and the high dispersion in technical efficiencies, it might be claimed that that there are important factors impeding the adequate use of the technology.

Figure 5.1 - Model J7: efficiency scores for the individual farms in Waikato-Taranaki



5.3 Canterbury-Southland

The preferred model for the Canterbury-Southland region is a translog with neutral technical change. Estimates of the parameters associated with the stochastic frontier are reported below (Table 5.6). The coefficients of the direct effects on labour and capital are significant at 10%. Three cross terms are significantly different from zero, confirming that there are some interactions among variables. Hence, the rejection of the Cobb-Douglas model as an adequate representation of the Canterbury-Southland region is justified. The sign of the coefficient of the time trend is negative. Meanwhile, the quadratic term on time is positive. Both coefficients are significant at 10%.

Finally, given that all the coefficients of the parameters that include area of farm, except the cross term area of farm and intermediate input, were not significant, the model was re-estimated with only three variables (labour, capital and intermediate input). Results indicate that the preferred functional form is still a translog with non-neutral technical change, time varying inefficiency and that inefficiency effects have a half-normal distribution. Given the results of the LR test, the hypothesis that area of farm can be excluded from the model was rejected at a 5% level of significance. The value of maximum likelihood estimate for γ is 0.3271 and is significant at 10%, indicating that technical inefficiency in the Canterbury-Southland sample is present but also that noise plays a significant role.

Finally, as for the Waikato-Taranaki stochastic frontier, the estimated value of the parameter μ_i is zero, indicating that technical inefficiency effects have a half-normal distribution. In contrast to the Waikato-Taranaki stochastic frontier, the value of maximum likelihood estimate for η is positive and significant, implying that technical efficiencies increase over time.

Table 5.6 – Model J7, data for Canterbury-Southland: maximum likelihood estimates for parameters of the stochastic frontier under VRS (variable returns to scale)

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	-0.3833	-0.0980
Area (A)	β_1	0.2862	0.3224
Labour (L)	β_2	2.3087	1.8211 *
Capital (K2)	β_3	-1.3234	-1.7941 *
Intermediate input (II)	β_4	0.7374	0.8792
Year (Y)	β_t	-0.0274	-1.8213 *
$(\text{Year})^2$	β_{tt}	0.0016	1.7696 *
$(A)^2$	β_{11}	-0.2079	-0.9433
(A) x (L)	β_{12}	-0.2273	-0.6051
(A) x (K2)	β_{13}	0.1871	0.5927
(A) x (II)	β_{14}	0.5560	1.8505 *
$(L)^2$	β_{22}	0.0377	0.1257
(L) x (K2)	β_{23}	0.0861	0.2388
(L) x (II)	β_{24}	-0.6968	-2.3305 **
$(K2)^2$	β_{33}	-0.1088	-0.5352
(K2) x (II)	β_{34}	0.3955	1.7866 *
$(II)^2$	β_{44}	0.0438	0.2673
Variance parameters			
Sigma	σ^2	0.0127	3.7229 **
Gamma	γ	0.3271	1.7703 *
Technical inefficiency effect	μ_i	Restricted to zero	
Time varying inefficiency	η	0.2085	4.7200 ***
Log-likelihood function		**114.21**	

Note: *** - significant at 1% level ($p<0.01$)
** - significant at 5% level ($p<0.05$)
* - significant at 10% level ($p<0.10$)

Whereas in the Cobb-Douglas function the coefficients on the parameters are the output elasticities, for the translog the coefficients on the first order terms cannot be directly interpreted as the elastictities. It should be noted that these elasticities are both farm- and time-specific. In order to conserve space, elasticities are evaluated at the mean of the data for each year (Table 5.7). When the translog function is estimated using the mean-differenced variables (Coelli et al., 2003), output elasticities are the coefficients on the first order terms. Estimates for parameters of the stochastic frontier under VRS using mean-differenced variables are reported in Appendix 1.

Over the period, labour appears to be the major determinant of dairy production growth with an average output elasticity of 0.39, followed by intermediate input at 0.29, capital at 0.098 and area of farm at 0.097 (Table 5.7). Estimates of the coefficients on the first order terms after mean-differencing the variables data indicate that all the elasticities are significant at 5% (Appendix 1, Table A1.1). However, the coefficient on the time-trend variable indicates that there is technical regress (negative technological progress). The frontier was shifting backwards at an annual rate of 1.14% per annum, and the effect is non-linear as indicated by the significant coefficient on the quadratic term.

On average for the period, a 1% increase in capital results in a growth of 0.1% in milk production *ceteris paribus*. Similarly, the outcome of a 1% increase in intermediate input[14] is an increase of 0.29% in milk production.

Table 5.7 - Model J7: elasticity estimates, rate of technical progress and return to scale for Canterbury-Southland

	Output elasticities				Returns to scale	Rate technical change
	Area	Labour	Capital	Intermediate input		
1996/97	0.0651	0.4693	0.0625	0.2358	0.8327	-0.0242
1997/98	0.0405	0.4734	0.0635	0.2369	0.8144	-0.0211
1998/99	0.0470	0.4750	0.0555	0.2684	0.8457	-0.0179
1999/00	0.0752	0.4481	0.0715	0.2625	0.8573	-0.0148
2000/01	0.1388	0.3843	0.0946	0.2872	0.9049	-0.0116
2001/02	0.1584	0.3064	0.1355	0.3283	0.9286	-0.0085
2002/03	0.1161	0.3315	0.1257	0.3252	0.8986	-0.0053
2003/04	0.1031	0.3326	0.1243	0.3395	0.8995	-0.0022
2004/05	0.1237	0.3011	0.1436	0.3324	0.9009	0.0010
Average	**0.0974**	**0.3891**	**0.0984**	**0.2919**	**0.8768**	**-0.0114**

Note: average values of output elasticities are estimated at sample mean over all years. The average rate of technical change corresponds to cumulative growth over the period.

[14] Inputs included are veterinary and shed expenses, fertilizer and feed

The elasticity of scale is found to be 0.87 indicating decreasing returns to scale. Returns to scale have been increasing over the period, from 0.83 to 0.90. Behind this development is a decline in the marginal elasticity of labour from 0.47 to 0.30, whereas the marginal output elasticities of area of farm, capital and intermediate input increase. The elasticity of area of farm increased from 0.065 to 0.12. Similarly, intermediate input and capital elasticities increased from 0.24 to 0.33 and from 0.06 to 0.14 respectively, confirming the positive coefficients of the interaction terms between these three variables (area of farm, capital and intermediate input).

The rate of technological progress at the frontier was negative (productivity slowdown) at decreasing rates. The productivity slowdown was more pronounced at the beginning of the period (-2.42% per annum), and it ended with a very small rate of technological progress (0.1% per annum). On average over the period, the frontier was regressing at 1.14% per annum as indicated above.

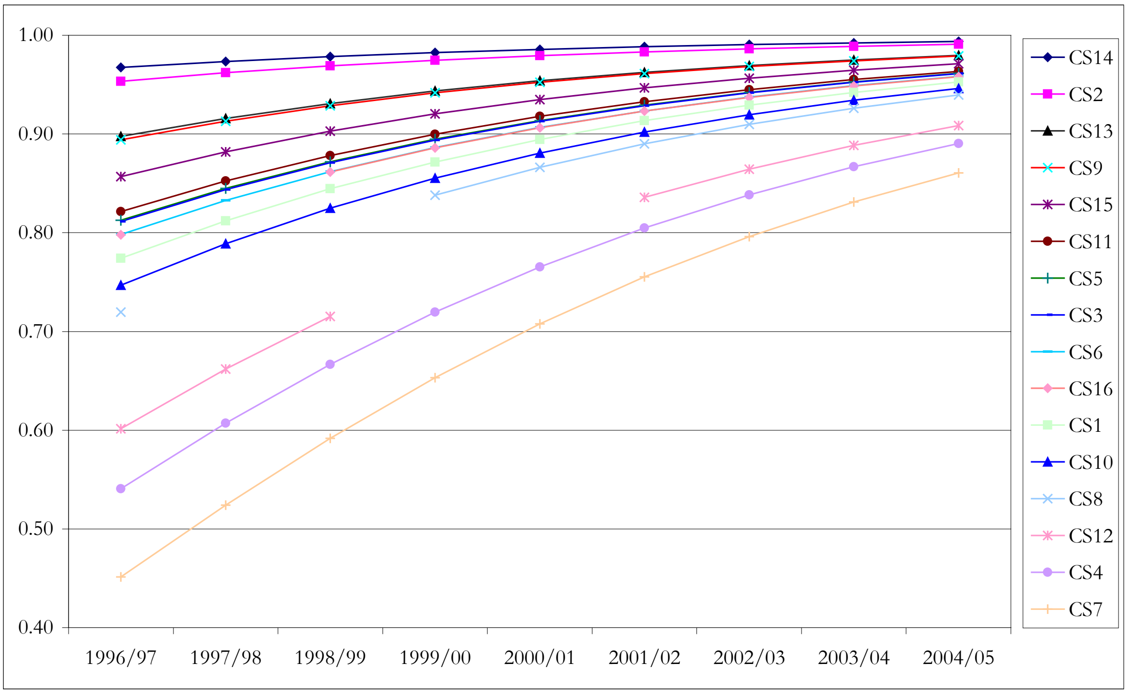
The mean overall technical efficiency is 88.4%. This result indicates that the volume of milk produced by the farms in the sample during the period could have been achieved with approximately 12% fewer resources, provided all farms were technically efficient. The positive sign on the coefficient on the parameter η implies that technical efficiencies increase over time (Figure 5.2). For the first season, average technical efficiency was 0.78 ranging between 0.97 and 0.45. Meanwhile, average technical efficiency climbed to 0.95 for the last season ranging between 0.994 and 0.861 (Table 5.8).

Table 5.8 - Model J7: estimates of technical efficiency by year for Canterbury-Southland

	Mean	Maximum	Minimum	St. deviation
1996/97	0.778	0.967	0.451	0.142
1997/98	0.815	0.973	0.524	0.132
1998/99	0.846	0.978	0.592	0.109
1999/00	0.877	0.982	0.653	0.088
2000/01	0.898	0.986	0.708	0.075
2001/02	0.911	0.988	0.755	0.064
2002/03	0.927	0.990	0.796	0.053
2003/04	0.940	0.992	0.831	0.044
2004/05	0.951	0.994	0.861	0.036

The dispersion in technical efficiencies of dairy farmers is considerable at the beginning of the period and, according to the assumed exponential model for the time varying inefficiency effects, they converged over time. Furthermore, insofar as the region experienced technical regress, backward farms (farms CS7, CS4 and CS12) were able to catch up with the frontier firms.

Figure 5.2 - Model J7: efficiency scores for the individual farms in Canterbury-Southland*(1)*



(1) Note: In years when particular farmers were not observed, no values of technical efficiency are calculated

5.4 Comparison of both regional models

The comparison of input elasticities and technical change across different regions is not straightforward because the production technologies are different for both regions. In fact, the pooled model was rejected in favour of a more general model that allows production technology to differ between regions (Section 1.1.4). Nevertheless, the marginal output elasticities evaluated at sample mean, the rate of technical progress and technical efficiency scores are presented.

The most important difference is found to be in the production function that represents the underlying production technology. Whereas a Cobb-Douglas best represented the production technology for Waikato-Taranaki farms, the more flexible translog function was the best representation of the Canterbury-Southland technology.

For the Waikato-Taranaki data, the estimated input elasticities, returns to scale and technical progress do not differ among farms or over time. In contrast, in the Canterbury-Southland data set, the estimated marginal elasticities, returns to scale and technical progress differ among farms and over time.

The marginal output elasticity of area of farm is at 0.28 for Waikato-Taranaki and at 0.097 for Canterbury-Southland. Labour contributes the most to output growth for Canterbury-Southland. However, the marginal output elasticity of labour is similar between regions, although a bit higher in the southern region: 0.31 for Waikato-Taranaki and 0.39 for Canterbury-Southland. Meanwhile, capital output elasticity for Waikato-Taranaki is at 0.038 and at 0.098 for Canterbury-Southland. Finally, intermediate input is the single most important contributor to output growth for Waikato-Taranaki, with a marginal output elasticity of 0.40, and the second-most important for Canterbury-Southland, with an elasticity of 0.29 (Table 5.9). In addition, Waikato-Taranaki is operating at increasing returns to scale (RTS) and Canterbury-Southland at decreasing returns to scale. However, RTS in Canterbury-Southland have been increasing over the period considered (Table 5.7).

Table 5.9 - Model J7: comparison of factor input elasticity estimates at sample mean

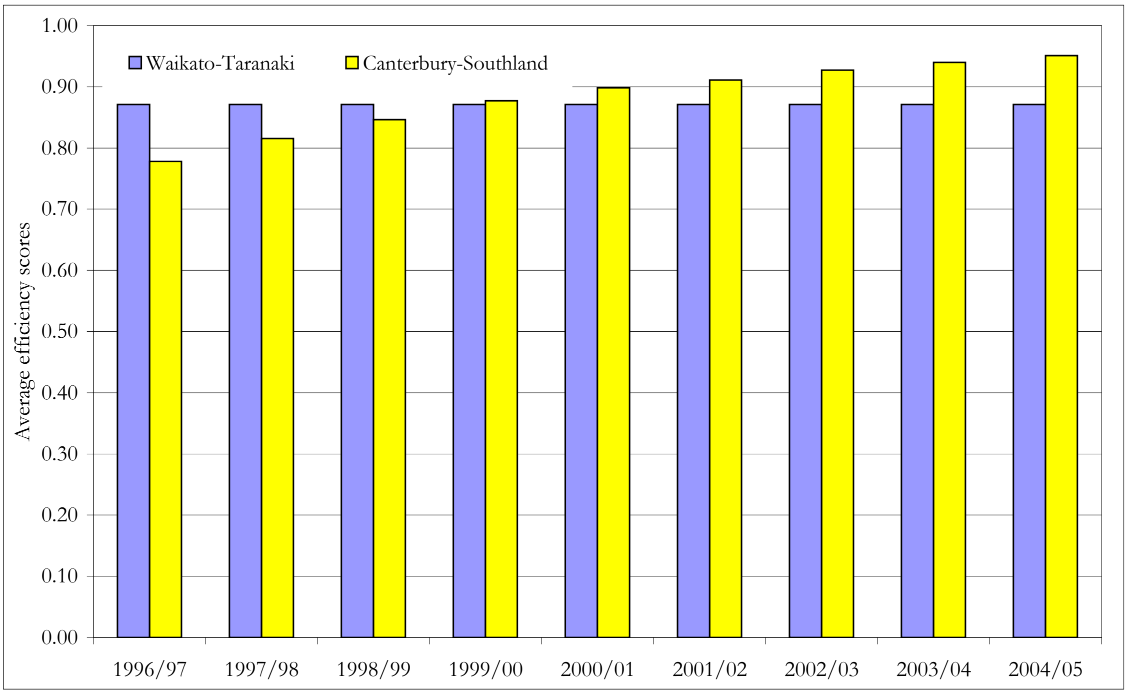
	Output elasticities				Returns to scale
	Area	Labour	Capital	Intermediate input	
Waikato-Taranaki	**0.2827**	**0.3104**	**0.0383**	**0.4052**	**1.036**
Relative contribution (%)	27%	30%	3%	39%	100%
Canterbury-Southland	**0.0974**	**0.3891**	**0.0984**	**0.2919**	**0.8768**
Relative contribution (%)	11%	44%	11%	33%	100%

The elasticity of output with respect to time is interpreted as the rate of exogenous technical change, i.e., a shift in the production function over time, *ceteris paribus*. Meanwhile, sampled farms in Waikato-Taranaki experienced a constant rate of technical progress (Table 5.5). Sampled farms in Canterbury-Southland exhibited neutral technical regress at a declining rate that became a small technical progress for the last season (Table 5.7).

Another important difference is found in the behaviour of technical efficiency over time. For Waikato-Taranaki, farm technical efficiencies are constant over time (Figure 5.1), whereas farms in Canterbury-Southland exhibited a progressive improvement (Figure 5.2). Consequently, the dispersion in farm technical efficiencies remained constant over time in the former region, but decreased in the latter region.

Average efficiency for Waikato-Taranaki farms was higher than Canterbury-Southland farms over the first three seasons of the period, but this was reversed in the last six years of the period (Figure 5.3). For the first season, average technical efficiency for Canterbury-Southland was 0.78, ranging between 0.97 and 0.45. Meanwhile, for the last season, average technical efficiency climbed to 0.95, ranging between 0.994 and 0.861 (Table 5.8). In contrast, average efficiency for Waikato-Taranaki remained at 0.87, ranging between 0.75 and 0.98 (Figure 5.1).

Figure 5.3 - Model J7: comparison of average efficiency score between Waikato-Taranaki and Canterbury-Southland



The policy implications of the different technical change and the behaviour over time of the farm efficiencies will be discussed in Chapter 9 where the decomposition of TFPG is undertaken.

CHAPTER 6

6 Results for Model L8

6.1 Determination of the preferred functional form

Model L8 was defined in terms of the following factor inputs: cows (number), labour (hours worked), area (hectares) and capital (K2, depreciation and interest on the stock of building and vehicles and machinery plus expenditure on repairs and maintenance and insurance).

6.1.1 All data pooled across both regions

Given the specifications of the stochastic frontier with time-varying inefficiency, various hypotheses were tested (Table 6.1). The translog production frontier was chosen based on the rejection of the Cobb-Douglas as inadequate. This implies that the input and substitution elasticities vary across farms. The hypothesis of no technical change and Hicks-neutral technical change were rejected, calling for the incorporation of a time trend (and its square term) and the time trend cross products with conventional factor inputs in the production function. The coefficient of the dummy introduced to capture the effects of the policy change was not significant ($t<2$). This result was confirmed by the LR test.

Given the specifications of the translog stochastic frontier with non-neutral technical change as the preferred functional form, it is evident that the traditional average response function, in which farms are assumed to be fully technical efficient, is not an adequate representation of the data (i.e., the null hypothesis H_0: $\gamma=\mu=\eta=0$ is rejected). Similarly, the null hypotheses that time-invariant models for farm effects apply are also rejected (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$ are rejected), indicating that technical efficiency levels vary significantly over time (Table 6.1). Finally, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was rejected.

Table 6.1 - Model L8, data for both regions: generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function

Null Hypothesis (*Ho*)	Log-likelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given pooled sample	244.17			
A Cobb-Douglas function is adequate	230.48	27.38	$\chi^2_{.05,\ 15} = 25.00$	Reject *Ho*
Technical change is neutral	237.56	13.22	$\chi^2_{.05,\ 4} = 9.49$	Reject *Ho*
NO technical change	233.12	22.1	$\chi^2_{.05,\ 6} = 12.6$	Reject *Ho*
Traditional average response function is adequate representation of the data ($\gamma=\mu=\eta=0$)	211.53	65.28	$\chi^2_{.05,\ 3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant $\mu=\eta=0$	238.85	10.64	$\chi^2_{.05,\ 2} = 5.99$	Reject *Ho*
Technical inefficiencies have a half-normal distribution $\mu=0$	241.32	5.7	$\chi^2_{.05,\ 1} = 3.84$	Reject *Ho*
Technical inefficiencies are time invariant $\eta=0$	241.21	5.92	$\chi^2_{.05,\ 1} = 3.84$	Reject *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

Next, the translog stochastic frontier model with non-neutral technical change was estimated with the regional dummy. The coefficient of the regional dummy has a value of

0.154 and it was significantly different from zero at 5% (t-value=4.562). This result was confirmed by the likelihood-ratio test (LR). Therefore, and as reported for Model J7 (Section 5.1.1), there is *a priori* evidence that the stochastic frontier model differs between regions. Furthermore, based on the sign of the dummy, it can be advanced that, given the production function defined by the input/output set, Canterbury-Southland sampled farms are, on average, 15.4% more productive than sampled farms in Waikato-Taranaki, *ceteris paribus*.

6.1.2 The Waikato-Taranaki sample

The value of the log-likelihood function, for the translog stochastic frontier model with the inefficiency effects for Waikato-Taranaki, is 128.53. The coefficient on the dummy introduced to capture the effects of the policy change was not significant as confirmed by the LR test. This result is similar to that of Model J7 (Section 5.1.2). Results of the different hypotheses tested are presented below (Table 6.2).

The first null hypothesis that the Cobb-Douglas is an adequate representation of the data was accepted. The hypothesis of Hicks-neutral technical change was not rejected against the non-neutral translog. However, with respect to the Cobb-Douglas, the Hicks-neutral translog was rejected. That is, all the cross term effects were jointly zero. It is evident that the traditional average response function, in which farms are assumed to be fully technical efficient, is not an adequate representation of the data (i.e., the null hypothesis H_0: $\gamma=\mu=\eta=0$ is rejected).

Table 6.2 - Model L8: data for Waikato-Taranaki: generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function

Null Hypothesis (*Ho*)	Log-likelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given pooled sample	128.53			
A Cobb-Douglas function is adequate	117.98	21.1	$\chi^2_{.05,\,15} = 25.00$	Accept *Ho*
Technical change is neutral	124.39	8.28	$\chi^2_{.05,\,4} = 9.49$	Accept *Ho*
Traditional average response function is adequate representation of the data (w.r.t. Cobb-Douglas) ($\gamma=\mu=\eta=0$)	113.44	9.08	$\chi^2_{.05,\,3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant (w.r.t. Cobb-Douglas) $\mu=\eta=0$	117.79	0.38	$\chi^2_{.05,\,2} = 5.99$	Accept *Ho*
Technical inefficiencies have a half-normal distribution (w.r.t. Cobb-Douglas) $\mu=0$	117.969	0.022	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*
Technical inefficiencies are time invariant (w.r.t. Cobb-Douglas) $\eta=0$	117.79	0.38	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

Conversely, the null hypotheses that time-invariant models for farm effects apply were accepted (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$), indicating that technical efficiency levels do not vary significantly over time (Table 6.2). Similarly, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was accepted, i.e., the technical inefficiency effects have an N $(0,\sigma^2)$ distribution.

6.1.3 The Canterbury-Southland sample

Given the specification of the translog stochastic frontier production function with time-varying inefficiency effects, for Canterbury-Southland sampled farms, the value of the log-likelihood function is 149.06 (Table 6.3). As for Model J7, according to the LR test, the coefficient on the dummy introduced to capture the effects of the policy change was not significant.

The null hypotheses that the Cobb-Douglas is an adequate representation, such that there is no technical change and that technical change is neutral were all rejected (Table 6.3), as was the case in the pooled sample and in the Waikato-Taranaki sample.

Given the specifications of the non-neutral translog stochastic frontier as the preferred functional form, it is evident that the traditional average response function, in which farms are assumed to be fully technical efficient, is not an adequate representation of the data (i.e., the null hypothesis H_0: $\gamma=\mu=\eta=0$ is rejected). Conversely, the null hypotheses that time-invariant models for farm effects apply are accepted (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$ are rejected), indicating that technical efficiency levels do not vary significantly over time (Table 6.3). Finally, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was accepted, i.e., the technical inefficiency effects have an $N(0,\sigma^2)$ distribution.

Table 6.3 - Model L8, data for Canterbury-Southland: generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function

Null Hypothesis (*Ho*)	Log-likelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given pooled sample	149.06			
A Cobb-Douglas function is adequate	124.76	48.6	$\chi^2_{.05,\,15} = 25.00$	Reject *Ho*
NO technical change	134.14	29.84	$\chi^2_{.05,\,6} = 12.6$	Reject *Ho*
Technical change is neutral	139.91	18.3	$\chi^2_{.05,\,4} = 9.49$	Reject *Ho*
Traditional average response function is adequate representation of the data ($\gamma=\mu=\eta=0$)	131.49	35.14	$\chi^2_{.05,\,3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant $\mu=\eta=0$	147.54	3.04	$\chi^2_{.05,\,2} = 5.99$	Accept *Ho*
Technical inefficiencies have a half-normal distribution $\mu=0$	148.90	0.32	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*
Technical inefficiencies are time invariant $\eta=0$	147.71	2.7	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

6.1.4 Testing the existence of a common frontier

As was previously mentioned, the value of the coefficient of the regional dummy included in the pooled sample indicates that both regions may not be operating under the same technology. The appropriateness of dividing the sample into two regions is tested by a likelihood-ratio test (Table 6.4).

Table 6.4 - Model L8: generalised likelihood-ratio tests of null hypotheses that regions share a common stochastic frontier production function

	Log-likelihood (parameters estimated)	LR-Test Statistic (degrees of freedom)	Critical value (0.05)	Decision
Waikato-Taranaki Cobb-Douglas $\mu=\eta=0$	117.79 (8)			
Canterbury-Southland Non-neutral technical change $\mu=\eta=0$	147.54 (23)			
H_A: ∑ [Log-likelihood (WT)]+ [Log-likelihood (CS)]	265.33 (31)			
Ho: Pooled sample Non-neutral technical change	244.17 (25)	-2*(244.17-265.33) = **42.32** df. (31-25=6)	$\chi^2_{.05, 6}$ = **12.6**	Reject *Ho*

Note that the number of parameters estimated for the pooled sample is 25: 21 parameters in the frontier function (20+1 for the constant), 2 for the variance terms (sigma and gamma), 1 for the scalar η and 1 for the inefficiency effects (u_i). In turn, the number of parameters estimated for Waikato-Taranaki model is 8: 6 parameters in the frontier function (5+1 for the constant), 2 for the variance terms (sigma and gamma). Finally, the number of parameters estimated for Canterbury-Southland model is 23: 21 parameters in the frontier function (20+1 for the constant) and 2 for the variance terms (sigma and gamma).

The outcome of the test indicates that the two regional stochastic frontiers for dairy farms are not the same, confirming the *a priori* result obtained by using the regional dummy in the pooled stochastic frontier (Section 6.1.1). Therefore, according to the log-likelihood ratio test, farm-level data in the two regions are not generated from a single production frontier or from the same underlying technology.

Maximum likelihood parameter estimates for both regions are presented below.

6.2 Waikato-Taranaki

As mentioned above, the preferred specification for the Waikato-Taranaki sample farms underlying technology is a Cobb-Douglas with non-neutral technical change, time invariant technical efficiency with a half-normal distribution (Table 6.2). Estimates of the parameters associated with the stochastic frontier are reported below.

All the coefficients on the production function are significantly different from zero at 5 %, with the exception of the time trend, which is not significantly different from zero (Table 6.5). The time-trend was deleted from the model, i.e., it was assumed that the parameters were time-invariant. The LR test confirmed the hypothesis that the parameters were time invariant. The coefficients on the parameters of the stochastic frontier remained unchanged to the third decimal place, i.e., factor input elastiticies do not vary. Furthermore, the hypotheses that η and μ_i were zero (individually or jointly) were accepted. However, the hypothesis of γ=0 could not be rejected, indicating that even in the presence of no technical progress and time-invariant technical efficiencies, the stochastic frontier production function is significantly different from the average response model. When the CRS model was estimated to evaluate the productivity growth, the sign on the time trend coefficient not only changed but also was significant. Hence, it was decided to maintain the time trend in the VRS model.

Both test statistics (σ^2 and γ) are significantly different from zero. The value of maximum likelihood estimate for γ is 0.4155 and is significant at 5 %. This test statistic reinforces the notion that technical inefficiency in the Waikato-Taranaki sample is present but also that noise plays a role. As indicated above, the estimated coefficients for η and μ_i were restricted to zero.

Table 6.5 - Model L8, data for Waikato-Taranaki: maximum likelihood estimates for parameters of the stochastic frontier under VRS (variable returns to scale)

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	4.6295	11.8959 ***
Cow (C)	β_1	1.0716	14.2902 ***
Labour (L)	β_2	0.1239	2.1232 **
Area (A)	β_3	-0.1517	-2.3206 **
Capital (K2)	β_4	0.1217	2.8074 **
Year (Y)	β_t	-0.0004	-0.1103
Variance parameters			
Sigma	σ^2	0.0133	3.8324 **
Gamma	γ	0.4155	2.5716 **
Technical inefficiency effect	μ_i	Restricted to zero	
Time-varying inefficiency	η	Restricted to zero	
Log-likelihood function		**117.79**	

Note: *** - significant at 1% level ($p<0.01$)

** - significant at 5% level ($p<0.05$)

* - significant at 10% level ($p<0.10$)

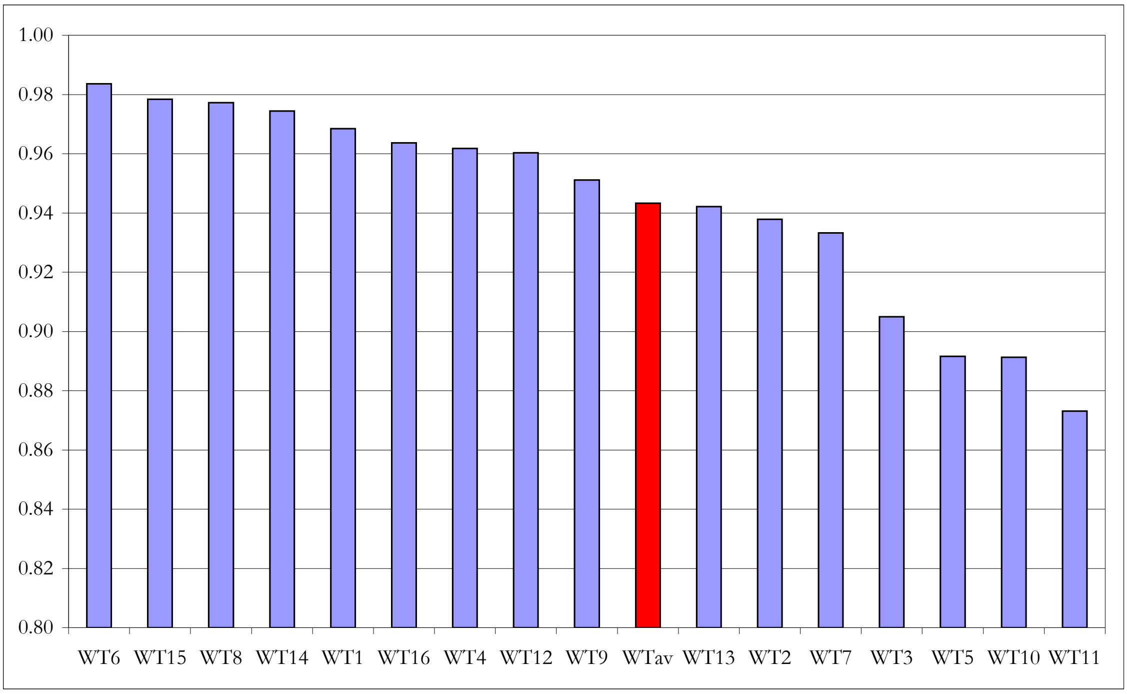
Given the function form, a Cobb-Douglas, the estimated coefficients are the output elasticities (Table 6.5). These are the same across all farms and over time. On average for the period, a 1% increase in the number of cows results in a growth of 1.07% in milk production *ceteris paribus*. Similarly, the outcome of a 1% increase in area of farm is a contraction of -0.15% in milk production *ceteris paribus*. The elasticity of scale is found to be 1.16, indicating increasing returns to scale in dairy farms.

Over the period, herd size appears to be the major determinant of dairy production growth, with an average output elasticity of 1.07, followed by labour at 0.12 and capital at 0.12. Interestingly, the estimated elasticity for area of farm turns out to be negative (-0.15). This may be the result of a progressive expansion of dairy into less suitable areas.

Over the period, both regions experienced a small absolute increase in dairy area. However, this increment coincided with an absolute decline in grassland and arable land area because of forestry developments and, particularly, new investments in property development and lifestyle blocks (MAF, 2001). Also, investments in property development and lifestyle blocks took place mostly in suburban areas, displacing dairy farmers. In turn, areas close to those newly developed areas increased their value. High land prices and the prospect that, in the near future, surrounding areas would also be converted into property development may induce farmers to invest in new, less suitable areas.

Given that the estimate of the parameter η is zero, the technical efficiencies were constant over time. This finding is not expected, given that the region experienced no technical progress. One possible reason may be that the time-varying inefficiency model used (Battese and Coelli, 1992, described in section 4.1, Chapter 4) is fairly restrictive in that it requires that the efficiencies of all firms follow a common trend, even though it allows for different levels.

Figure 6.1 - Model L8: efficiency scores for the individual farms in Waikato-Taranaki



The mean overall technical efficiency is 0.943, ranging between 0.984 and 0.873 (Figure 6.1). This result indicates that the volume of milk produced by the farms in the sample during the period could have been achieved with approximately 6% fewer resources, provided all farms were technically efficient.

It can also be seen that the dispersion in farm technical efficiency is low (the coefficient of variation is 3.7%). Furthermore, nine farms had a technical efficiency higher than 0.95, and only three had efficiency estimates lower than 0.90. This indicates that the technology defined by this input/output set is being used adequately. In turn, the fact that technical progress at the frontier was zero and that farm efficiency scores are high (i.e., technology is being applied adequately) leads to the conclusion that farms in the sample need a new technological paradigm to be able to increase productivity.

6.3 Canterbury-Southland

The preferred model for the Canterbury-Southland region is a translog with non-neutral technical change. Estimates of the parameters associated with the stochastic frontier are reported below (Table 6.6). Only one cross term is significantly different from zero as well as the square term on capital. The sign on the coefficient of the time trend is positive but not significant. Meanwhile, the square term on time is negative and not significant as well. Two of the interaction terms between time and factor inputs are significant at 5%. However, as mentioned above (Table 6.3), the Cobb-Douglas functional form was rejected in lieu of the translog, indicating that even though the individual coefficients might not be significant, taken together they have a better explanatory power. Furthermore, the simplified translog functional form was also rejected in favour of the translog. The simplified translog model assumes that inputs are separable from each other but not from time, i.e., the entire cross terms and the quadratic terms were assumed to be zero (Ahmad and Bravo-Ureta, 1996).

The value of maximum likelihood estimate for γ is 0.7890 and is significant at 5 %, i.e., technical inefficiency is present. Finally, the estimated value of the parameter μ_i is zero, indicating that technical inefficiency effects have a half-normal distribution and the value of maximum likelihood estimate for η is zero, i.e., technical efficiency is constant over time.

Table 6.6 - Model L8, data for Canterbury-Southland: maximum likelihood estimates for parameters of the stochastic frontier under VRS (variable returns to scale)

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	3.5331	1.1011
Cow (C)	β_1	0.0830	0.0617
Labour (L)	β_2	1.6128	1.1852
Area (A)	β_3	0.2342	0.3179
Capital (K2)	β_4	-1.1469	-1.6092
Year (Y)	β_t	0.1079	1.2387
$(\text{Year})^2$	β_{tt}	-0.0018	-1.2852
(C) x (Y)	β_{1t}	0.0156	0.5489
(L) x (Y)	β_{2t}	-0.0078	-0.4076
(A) x (Y)	β_{3t}	-0.0622	-4.1407 **
(K2) x (Y)	β_{4t}	0.0470	3.0437 **
$(C)^2$	β_{11}	-0.0159	-0.0278
(C) x (L)	β_{12}	0.3081	0.4042
(C) x (A)	β_{13}	-0.0604	-0.1125
(C) x (K2)	β_{14}	-0.1355	-0.3078
$(L)^2$	β_{22}	-0.2505	-0.6960
(L) x (A)	β_{23}	-0.2201	-0.6626
(L) x (K2)	β_{24}	0.1149	0.3536
$(A)^2$	β_{33}	-0.0900	-0.3434
(A) x (K2)	β_{34}	0.7282	2.6862 **
$(K2)^2$	β_{44}	-0.2182	-1.7955 *
Variance parameters			
Sigma	σ^2	0.0252	2.7570 **
Gamma	γ	0.7890	9.6032 ***
Technical inefficiency effect	μ_i	0	
Time-varying inefficiency	η	0	
Log-likelihood function		**147.54**	

Note: *** - significant at 1% level ($p<0.01$)

** - significant at 5% level ($p<0.05$)

* - significant at 10% level ($p<0.10$)

Over the period, herd size appeared to be the major determinant of dairy production growth with an average output elasticity of 0.86, followed by area of farm at 0.26 and labour at 0.07. Interestingly, the marginal output elasticity of capital is negative at -0.14

(Table 6.7). It is worth mentioning that the same measure of capital yielded an output elasticity of 0.098 in Model J7 (Table 5.7).

Average elasticities for herd size and area of farm are significant at 5%, capital elasticity is significant at 10% and finally, labour elasticity is not significant (Appendix 1, Table A1.2). However, insignificant estimates of labour elasticity have been reported before (Bravo-Ureta, 1986 and Cuesta, 2000). The coefficient on the time-trend variable indicates that the frontier was shifting upwards at an annual rate of 2.18% per annum. The coefficient on the quadratic term on time was not significant (Appendix 1, Table A1.2).

On average for the period, a 1% increase in the number of cows results in a growth of 0.86% in milk production *ceteris paribus*. Similarly, the outcome of a 1% increase in capital is a reduction of 0.14% in milk production. The negative elasticity for capital suggests that there is considerable surplus in the use of this input. This particular finding may be related to the fact that this region is characterised by recently developed dairy farms that may have incurred significant initial capital investments. Another plausible explanation is related to the infrastructure of services, which is dictated by the number of farms. The small number of farms may be preventing the development of different services connected to dairy, for example, seeding, harvesting, silage, etc. Hence, farmers have to acquire all the machinery to perform those tasks, thereby increasing their expenditure of capital. However, more research is needed to endorse this assumption.

The elasticity of scale is found to be 1.05, indicating increasing returns to scale in dairy farms. Furthermore, returns to scale have been increasing slightly over time. The marginal elasticity of herd size remained almost constant over the period. Conversely, the marginal output elasticity of area increased from 0.18 to 0.33 and the marginal output elasticity of labour declined from 0.08 to 0.03. Finally, the marginal output elasticity of capital dropped from -0.126 to -0.174 by season 2000/01 and increased over the second half of the period to -0.136.

Table 6.7 - Model L8: elasticity estimates, rate of technical progress and return to scale for Canterbury-Southland

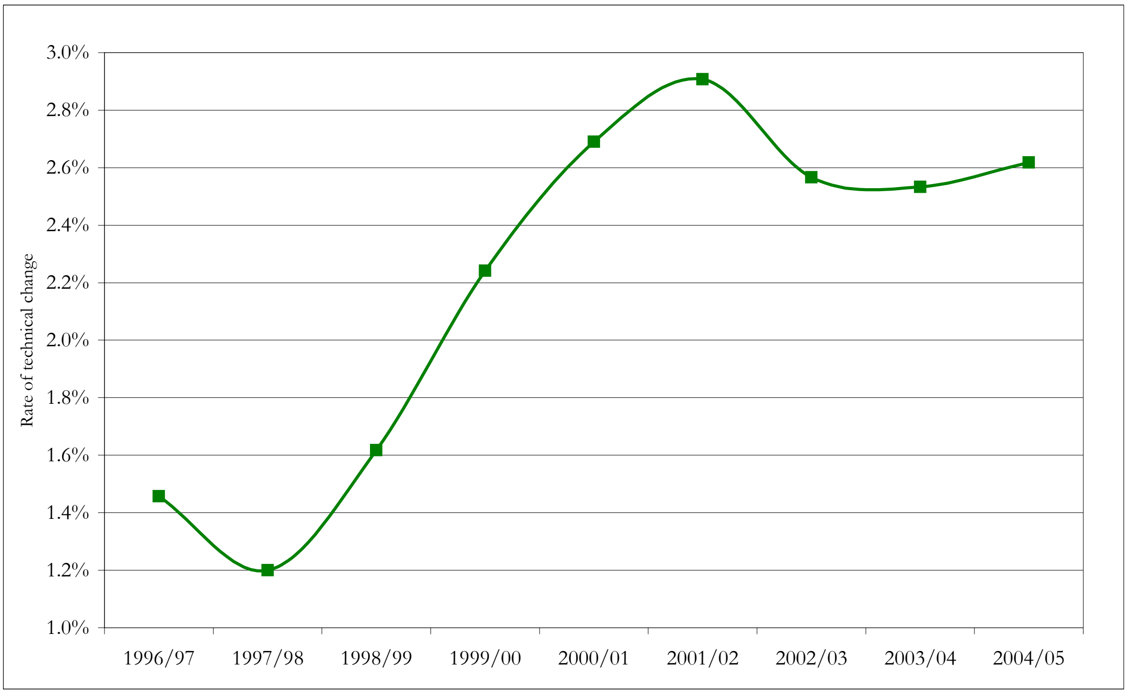
	Output elasticities				Returns to scale	Rate of technical change
	Cows	Labour	Area	Capital		
1996/97	0.8600	0.0841	0.1825	-0.1265	1.0001	0.0146
1997/98	0.8651	0.0686	0.1795	-0.1081	1.0051	0.0120
1998/99	0.8525	0.0878	0.2007	-0.1191	1.0220	0.0162
1999/00	0.8522	0.1012	0.1911	-0.1272	1.0174	0.0224
2000/01	0.8526	0.0948	0.2696	-0.1740	1.0430	0.0269
2001/02	0.8596	0.0616	0.3239	-0.1633	1.0819	0.0291
2002/03	0.8649	0.0467	0.3147	-0.1414	1.0848	0.0257
2003/04	0.8636	0.0441	0.3239	-0.1349	1.0968	0.0253
2004/05	0.8700	0.0339	0.3277	-0.1364	1.0952	0.0262
Average	**0.8602**	**0.0687**	**0.2590**	**-0.1371**	**1.0507**	**0.0218**

Note: average values of output elasticities are estimated at sample mean. The average rate of technical change corresponds to cumulative growth over the period.

The rate of technical change at the frontier was positive over the whole period. It gradually increased from 1.46% at the beginning of the period to 2.91% by season 2001/02 and then declined slightly to 2.62% by the last season (Figure 6.2). As a result, the rate of change of the production frontier was at 2.18% per annum. The small decline in the rate of technical progress at the frontier in season 1997/98 may be the result of the drought experienced by the region.

The progressive increase in the rate of technical progress at the frontier from the beginning of the period up to season 2001/02 may be rooted in the need to increase productivity and hence improve profitability. The average milk payout in real terms from seasons 1996/97 to 1999/00 was $4.15 per kg milksolids, whereas the historical milk payout in real terms was $4.27, from 1985 to 1999. The downturn over the last three seasons may be the consequence of the high profitability, due to unprecedented higher milk prices, which may have reduced the incentives to increase productivity. Higher milk prices induced an expansion in production sustained on more than proportional increase in input use, translated into a deterioration of the ratio output: input (productivity). The average milk payout for the period 2000/01 to 2004/05 milk price stood at $4.80 per kg milksolids, an increase of 15.8% over the previous seasons of the period considered. Furthermore, season 2001/02 marked the highest payout, in real terms, over the last 20 years.

Figure 6.2 - Model L8: annual rate of technical progress for Canterbury-Southland

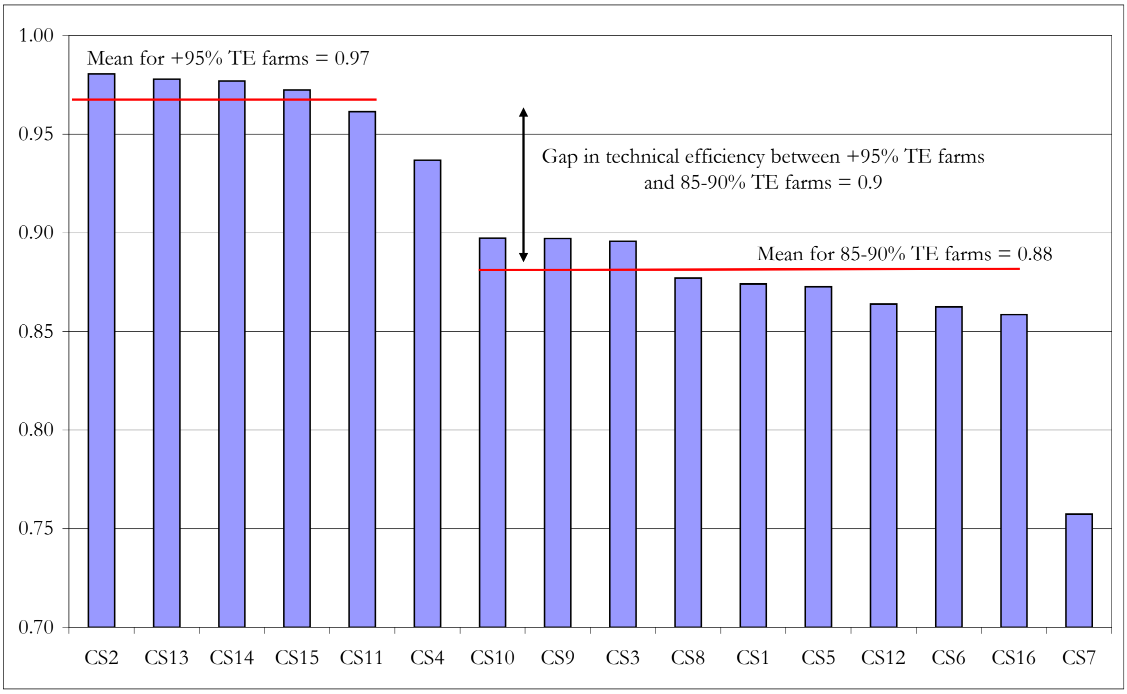


As indicated above, the technical efficiencies were time-invariant (the estimate of the parameter η was zero). However, the restrictions imposed by the model applied (Battese and Coelli, 1992, described in section 4.1, Chapter 4) may prevent the capture of efficiency improvements. Alternatively, it may be the result of the active annual rate of technical progress at the frontier.

The mean overall technical efficiency is 0.89, ranging between 0.73 and 0.98 (Figure 6.3). On average, the volume of milk produced by the farms in the sample during the period could have been achieved with approximately 10% fewer resources, provided that all farms were technically efficient.

These data indicate that there exists considerable variation in the efficiencies of dairy farmers in Canterbury-Southland. The distribution of technical efficiency estimates by Model L8 illustrates that nine farms have efficiency estimates in the range 85%–90% (Figure 9.4). Average efficiency for those farms is 0.88. Distance from best-practice farms is almost 10%, and from the next most efficient farm it is 5%. This implies that, on average, milk production from those farms could have been increased by 10% or 5%, with the same level of resources used, provided they improve their efficiency at least to the level where the other farms are operating.

Figure 6.3 - Model L8: efficiency scores for individual farms in Canterbury-Southland



Relative to the underlying technology defined by Model L8, results seem to indicate that technical progress at the frontier is 2.18% per annum, and that many farms are still unable to apply this technology adequately, insofar as gains in technical efficiency change are nil and the dispersion of farm technical efficiency is relatively high (Figure 6.3).

6.4 Comparison of both regional models

Given that the production technology differs between regions (Section 6.1.4) the comparison of input elasticities and technical change across regions is not straightforward. However, the marginal output elasticities evaluated at sample mean, the rate of technical progress and technical efficiency scores are presented (Table 6.8).

The most important difference is found to be in the production function that represents the underlying production technology. A Cobb-Douglas for Waikato-Taranaki sampled farms best represented the production technology; the more flexible translog function was used to represent the Canterbury-Southland technology.

For Waikato-Taranaki data set, the estimated input elasticities, returns to scale and technical progress are constant across farms and over time. Furthermore, there is no technical progress at the frontier. In the Canterbury-Southland data set, the estimated marginal elasticities, returns to scale and technical progress are all farm-specific and also vary over time. Moreover, technical progress at the frontier is non-neutral.

Number of cows is the single most important input for both regions (Table 6.8). However, marginal output elasticity of cows is 1.07 for Waikato-Taranaki and 0.86 for Canterbury-Southland. The marginal output elasticity of labour is 0.12 for Waikato-Taranaki and 0.068 for Canterbury-Southland. Meanwhile, the marginal output elasticities of area of farm and capital have different signs in the two regions.

Table 6.8 - Model L8: comparison of factor input elasticity estimates at sample mean

	Output elasticities				Returns to scale
	Cows	Labour	Area	Capital	
Waikato-Taranaki	**1.0716**	**0.1239**	**-0.1517**	**0.1217**	**1.1655**
Relative contribution (%)	92%	11%	-13%	10%	100%
Canterbury-Southland	**0.8602**	**0.0687**	**0.2590**	**-0.1371**	**1.0507**
Relative contribution (%)	82%	7%	25%	-13%	100%

The elasticity of area of farm is at -0.15 for Waikato-Taranaki and at 0.259 for Canterbury-Southland. As explained above, the negative elasticity for area of farm in Waikato-Taranaki might be the result of the expansion of dairy into less suitable areas. Conversely, the positive elasticity for Canterbury-Southland might be indicating that expansion into new areas is still feasible.

Capital output elasticity is 0.12 for Waikato-Taranaki and -0.137 for Canterbury-Southland. As explained above, the different sign in the capital output elasticity may be related to the degree of development of dairy farming in both regions. Most dairy farms in Canterbury-

Southland have been recently developed with significant initial capital investments. For example, pasture irrigation is frequent in Canterbury. Another possible explanation of the different sign in capital elasticity is the degree of development of the infrastructure of services. The number of farms in Waikato-Taranaki is much higher than in Canterbury-Southland. Hence, whereas in the former region, infrastructure of services may be well developed and services easily available, in the latter, farmers need to rely on their own machinery to perform the different tasks. Finally, both regions are operating at increasing returns to scale. However, Canterbury-Southland has been experiencing an increase in the returns to scale over the period considered (Table 6.7).

Average efficiency for Waikato-Taranaki farms was higher than for Canterbury-Southland farms. Furthermore, farm efficiency estimates are less dispersed for the former region than for the latter (Table 6.9). The higher average efficiency and the lower dispersion exhibited by Waikato-Taranaki farmers may indicate that these long-established farms all have a better mastery of the technology applied (9 out of 16 have efficiencies higher than 0.95) than farmers in Canterbury-Southland, where only 5 farms ranked high. Alternatively, it may be the result of the active annual rate of technical progress at the frontier exhibited by Canterbury-Southland vis-à-vis Waikato-Taranaki that did not experience technical progress.

Table 6.9 - Model L8: average efficiency scores and farm efficiency distribution between regions

Efficiency range	Number of farms	
	Waikato-Taranaki	Canterbury-Southland
0.97-1	4	3
0.95-0.97	5	2
0.90-0.95	4	2
0.85-0.90	3	7
0.80-0.85		0
<0.80		2
Average	0.943	0.894
Maximum	0.984	0.981
Minimum	0.873	0.735
Coeff. Var.	3.74%	7.77%

CHAPTER 7

7 Results for Model Y5

7.1 Determination of the preferred functional form

Model Y5 was defined in terms of the following factor inputs: capital (K2, depreciation and interest on the stock of building and vehicles and machinery plus expenditure on repairs and maintenance), labour (hours worked), feed expenditure (deflated by the corresponding price index) and fertiliser and weed expenditure (deflated by the corresponding price index).

7.1.1 All data pooled across both regions

Empirical results were obtained by using the stochastic frontier production model with time-varying inefficiency effects defined above (Chapter 4) and various hypotheses were tested (Table 7.1). The translog production frontier was chosen based on the rejection of the Cobb-Douglas as inadequate. These imply that the input and substitution elasticities vary across farms. The hypothesis of no technical change and Hicks-neutral technical change were rejected, calling for the incorporation of a time trend (and its square term) and the time trend cross products with conventional factor inputs in the production function.

Given the specifications of the translog stochastic frontier with non-neutral technical change as the preferred functional form, it is evident that the traditional average response function, in which farms are assumed to be fully technical efficient, is not an adequate representation of the data (i.e., the null hypothesis H_0: $\gamma=\mu=\eta=0$ is rejected) (Table 7.1).

Table 7.1 - Model Y5, data for both regions: generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function

Null Hypothesis (*Ho*)	Log-likelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given pooled sample With dummy for policy change	183.799			
A Cobb-Douglas function is adequate	166.206	35.18	$\chi^2_{.05,\,15} = 25.00$	Reject *Ho*
Technical change is neutral	178.02	11.56	$\chi^2_{.05,\,4} = 9.49$	Reject *Ho*
NO technical change	176.02	15.56	$\chi^2_{.05,\,6} = 12.6$	Reject *Ho*
Traditional average response function is adequate representation of the data ($\gamma=\mu=\eta=0$)	147.299	73.00	$\chi^2_{.05,\,3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant $\mu=\eta=0$	180.64	6.34	$\chi^2_{.05,\,2} = 5.99$	Reject *Ho*
Technical inefficiencies have a half-normal distribution $\mu=0$	182.68	2.24	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*
Technical inefficiencies are time invariant $\eta=0$	181.71	4.18	$\chi^2_{.05,\,1} = 3.84$	Reject *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

Similarly, the null hypotheses that time-invariant models for farm effects apply are also rejected (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$ are rejected), indicating that technical efficiency levels vary significantly over time. Finally, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was accepted (Table 7.1).

The coefficient of the dummy introduced to capture the effects of the policy change[15] was significant under all the hypotheses tested. For the preferred specification, i.e., translog stochastic frontier with non-neutral technical change and time-varying inefficiency effects with half-normal distribution, the coefficient of the dummy was -0.084 and significant at 5% (t=2.698). This latter result was further confirmed by the LR test. Therefore, relative to the base period 1996/97 to 2000/01 (prior to the creation of Fonterra), farms in the sample were, on average, 8.4% less productive in the period 2001–2005.

Next, the regional dummy was incorporated into the model. The coefficient of the regional dummy has a value of 0.1831 and it was significantly different from zero at 5% (t-value=4.8988). This result was also confirmed by the likelihood-ratio test (LR). Therefore, based on this result, there is *a priori* evidence that the stochastic frontier model differs between regions. Furthermore, based on the sign of the dummy, it can be advanced that, relative to Waikato-Taranaki sampled farms, Canterbury-Southland sampled farms are, on average, 16% more productive. Finally, the introduction of regional dummy changed slightly the coefficient on the dummy for policy change. The coefficient was -0.0711 and was significant at 5% (t= 2.3795), implying that relative to the base period (before the creation of Fonterra), farms in the sample were, on average, 7.11% less productive in 2001–2005.

7.1.2 The Waikato-Taranaki sample

The value of the log-likelihood function for the translog stochastic frontier model with time varying inefficiency effects for Waikato-Taranaki is 106.27. Results of the different hypotheses tested are presented below (Table 7.2).

[15] As mentioned above (Section 4.7), this dummy variable may also be capturing effects other than change in the institutional organization of the dairy industry, called for simplicity policy change.

Table 7.2 - Model Y5, data for Waikato-Taranaki: generalized likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function

Null Hypothesis (*Ho*)	Log-likelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given pooled sample	106.27			
A Cobb-Douglas function is adequate	97.37	17.8	$\chi^2_{.05,\,15} = 25.00$	Accept *Ho*
Technical change is neutral	99.68	13.18	$\chi^2_{.05,\,4} = 9.49$	Reject *Ho*
NO technical change	98.21	16.12	$\chi^2_{.05,\,6} = 12.6$	Reject *Ho*
Traditional average response function is adequate representation of the data (w.r.t. Cobb-Douglas) ($\gamma=\mu=\eta=0$)	78.778	37.18	$\chi^2_{.05,\,3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant (w.r.t. Cobb-Douglas) $\mu=\eta=0$	94.978	4.784	$\chi^2_{.05,\,2} = 5.99$	Accept *Ho*
Technical inefficiencies have a half-normal distribution (w.r.t. Cobb-Douglas) $\mu=0$	94.99	4.76	$\chi^2_{.05,\,1} = 3.84$	Reject *Ho*
Technical inefficiencies are time invariant (w.r.t. Cobb-Douglas) $\eta=0$	97.363	0.014	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

The Cobb-Douglas function was accepted in lieu of the translog to represent the underlying production technology. These imply that the input and substitution elasticities do not differ between farms or between periods. Both the hypotheses of no technical change and Hicks-neutral technical change were rejected.

Given the specifications of the Cobb-Douglas stochastic frontier as the preferred functional form, it is evident that the traditional average response function, in which farms are assumed to be fully technical efficient, is not an adequate representation of the data (i.e., the null hypothesis H_0: $\gamma=\mu=\eta=0$ is rejected). The null hypotheses that time-invariant models for farm effects apply are accepted (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$ are accepted), indicating that technical efficiency levels do not differ significantly over time (Table 7.2). However, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was rejected. Furthermore, given the hypothesis that the yearly time effects are time-invariant (H_0: $\eta=0$ is accepted), the half-normal distribution is not appropriate to define the distribution of the farm effects. Therefore, on the basis of these results, the hypothesis of time-invariant technical efficiencies was accepted. Finally, the coefficient of the dummy introduced to capture the effects of the policy change was not significant (t-statistic<2) either for the translog or the CD functional forms. Both were confirmed by the LR test.

7.1.3 The Canterbury-Southland sample

Given the specification of the translog stochastic frontier production function with time varying inefficiency effects, the value of the log-likelihood function is 121.288 for Canterbury-Southland sampled farms (Table 7.3). In contrast to the other region, the coefficient of the dummy for policy change was significantly different from zero (t-statistic>2) and was confirmed by the LR test.

The hypothesis that the Cobb-Douglas is an adequate representation of the production technology was rejected by the data (Table 7.3). These imply that the input and substitution elasticities differ among farms. Furthermore, the hypothesis of no technical change and Hicks-neutral technical change were rejected, calling for the incorporation of a time trend (and its square term) and the time trend cross products with conventional factor inputs in the production function.

Given the specifications of the translog stochastic frontier with non-neutral technical change as the preferred functional form, it is evident that the traditional average response function, in which farms are assumed to be fully technical efficient, is not an adequate representation of the data (i.e., the null hypothesis H_0: $\gamma=\mu=\eta=0$ is rejected). Similarly, the null hypotheses that time-invariant models for farm effects apply are also rejected (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$ are rejected), indicating that technical efficiency levels differ significantly over time. Finally, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was accepted (Table 7.3).

Given that the half-normal distribution was assumed appropriate to define the distribution of the farm effects, the maximum likelihood estimate for the coefficient on the dummy for the policy change was -0.0717 and was significant at 10% (t=-1.8384). The coefficient was found to be different from zero by the LR test. Hence, the policy change was not neutral in regard to its effect on the sampled farms in Canterbury-Southland. Relative to the base period (before the creation of Fonterra), dairy farms in the sample were, on average, 7.17% less productive in 2001–2005. Finally, the coefficient of the dummy for policy change for sampled farms in Canterbury-Southland (-0.0717) conforms to that estimated for the pooled sampled with the regional dummy (-0.0711), suggesting that sampled farms in Waikato-Taranaki were not affected by the policy change.

Table 7.3 - Model Y5, data for Canterbury-Southland: generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function

Null Hypothesis (*Ho*)	Log-likelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given pooled sample With dummy for policy change	121.288			
A Cobb-Douglas function is adequate	91.35	59.87	$\chi^2_{.05,\,15} = 25.00$	Reject *Ho*
Technical change is neutral	115.27	12.036	$\chi^2_{.05,\,4} = 9.49$	Reject *Ho*
NO technical change	112.01	18.556	$\chi^2_{.05,\,6} = 12.6$	Reject *Ho*
Traditional average response function is adequate representation of the data ($\gamma=\mu=\eta=0$)	94.34	53.89	$\chi^2_{.05,\,3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant $\mu=\eta=0$	105.51	31.556	$\chi^2_{.05,\,2} = 5.99$	Reject *Ho*
Technical inefficiencies have a half-normal distribution $\mu=0$	121.158	0.26	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*
Technical inefficiencies are time invariant $\eta=0$	105.72	31.14	$\chi^2_{.05,\,1} = 3.84$	Reject *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

7.1.4 Testing the existence of a common frontier

As was previously mentioned, the value of the coefficient of the regional dummy included in the pooled sample indicates that both regions may not be operating under the same technology. For model Y5, the preferred stochastic frontier models are specified below (Table 7.4). Note that the number of parameters estimated for the pooled sample and for Canterbury-Southland model is 25 (21 parameters in the frontier function (20+1 for the constant), 2 for the variance terms (sigma and gamma), 1 for the scalar η and 1 for the dummy for policy change). In turn, the number of parameters estimated for Waikato-Taranaki model is 9 (6 parameters in the frontier function (5+1 for the constant), 2 for the variance terms (sigma and gamma) and 1 for the inefficiency effects (u_i)).

Table 7.4 - Model Y5, generalised likelihood-ratio tests of null hypotheses that regions share a common stochastic frontier production function

	Log-likelihood (parameters estimated)	LR-Test Statistic (degrees of freedom)	Critical value (0.05)	Decision
Waikato-Taranaki Cobb-Douglas η=0	97.363 (9)			
Canterbury-Southland Non-neutral technical change with dummy for policy change and μ=0	121.158 (25)			
H_A: $\sum$ [Log-likelihood (WT)]+ [Log-likelihood (CS)]	218.521 (34)			
Ho: Pooled sample Non-neutral technical change with dummy for policy change μ=0	182.685 (25)	-2*(182.685-218.521) = **71.67** df. (34-25=9)	$\chi^2_{.05,9}$ = **16.9**	Reject *Ho*

The outcome of the test indicates that the two regional stochastic frontiers for dairy farms are not the same, supporting the *a priori* result obtained by using the regional dummy in the pooled stochastic frontier. Therefore, according to the log-likelihood ratio test, farm-level data in the two regions are not generated from a single production frontier and the same underlying technology. Maximum likelihood parameter estimates for both regions are presented below.

7.2 Waikato-Taranaki

As was mentioned above, the preferred model for the Waikato-Taranaki region is a Cobb-Douglas with time-invariant inefficiency. All the coefficients are significantly different from zero at 5%, except the time trend that is significant at 10%. Both test statistics (σ^2 and γ) are significantly different from zero, as well as the maximum likelihood estimate for μ_i. The value of maximum likelihood estimate for η is zero, i.e., technical efficiency is constant over time. Given the function form, a Cobb-Douglas, the estimated coefficients are the output elasticities (Table 5). These do not differ between farms or over time. Furthermore, technical progress is Hicks-neutral.

Table 7.5 - Model Y5, data for Waikato-Taranaki: maximum likelihood estimates for parameters of the stochastic frontier under VRS (variable returns to scale)

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	6.3101	11.0010 ***
Capital (K2)	β_1	0.1647	2.9542 **
Labour (L)	β_2	0.3913	5.2041 ***
Feed (FE)	β_3	0.2031	7.3520 ***
Fertiliser (FT)	β_4	0.2473	5.8596 ***
Year (Y)	β_t	0.0041	1.7706 *
Variance parameters			
Sigma	σ^2	0.0195	3.6873 **
Gamma	γ	0.5195	4.6873 **
Technical inefficiency effect	μ_i	0.2013	3.5231 **
Time-varying inefficiency	η	Restricted to zero	
Log-likelihood function		**97.363**	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

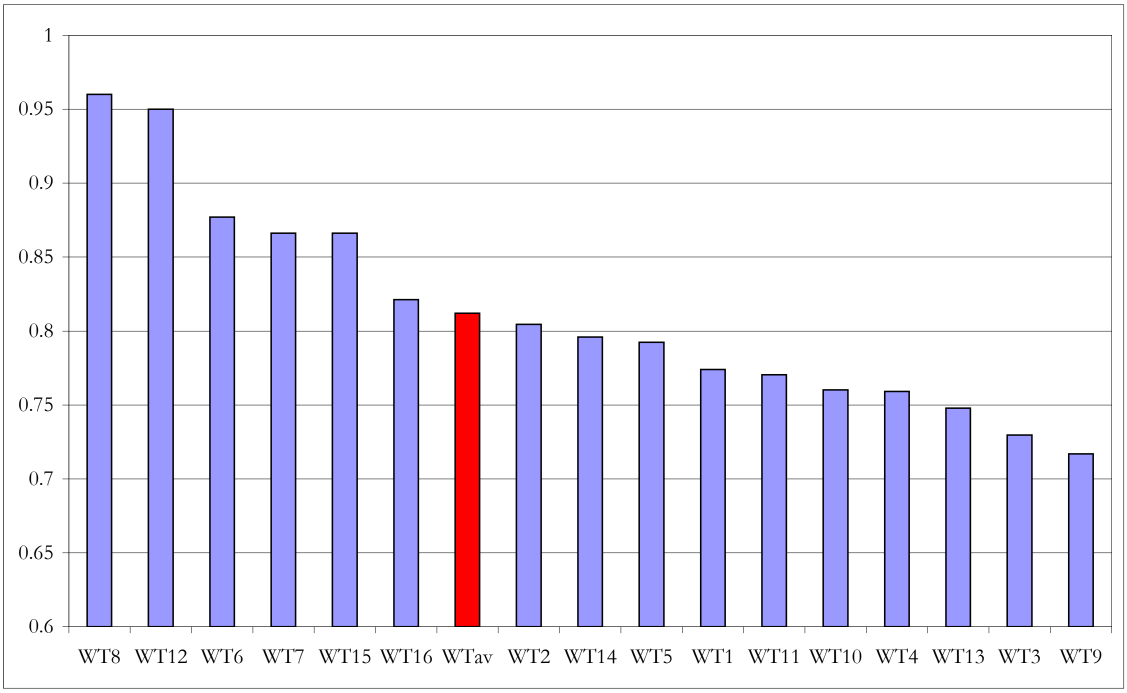
Over the period, labour appears to be the major determinant of dairy production growth, with an average output elasticity of 0.39, followed by fertiliser at 0.25, feed at 0.20 and capital at 0.16. On average for the period, a 1% increase in hours worked results in a growth of 0.39% in milk production *ceteris paribus*. Similarly, the outcome of a 1% increase in capital is an expansion of 0.16% in milk production. The elasticity of scale was 1.0063, indicating constant returns to scale in dairy farms.

The frontier was shifting upwards (the region experienced technical progress) at a constant rate. The rate of exogenous technical progress is found to be increasing productivity by 0.41% per annum.

Given that the estimate of the parameter η is zero, the technical efficiencies were constant over time. The mean overall technical efficiency is 0.81, ranging between 0.72 and 0.96 (Figure 7.1). This result indicates that the volume of milk produced by the farms in the sample during the period could have been achieved with approximately 19% fewer resources, if all farms had been technically efficient.

The dispersion in technical efficiencies among dairy farmers is considerable. Furthermore, it can be seen that only two farms ranked high in technical efficiency (more than 95%), while three others have technical efficiencies higher than 85%. Given the small rate of technical progress and the high dispersion in technical efficiencies and bearing in mind the restrictions imposed by the model, it appears that there are important factors impeding the adequate use of the technology. A similar conclusion was found for Model J7 (Section 5.2, Chapter 5).

Figure 7.1 - Model Y5: efficiency scores for the individual farms in Waikato-Taranaki



7.3 Canterbury-Southland

The preferred model for the Canterbury-Southland region is a translog with non-neutral technical change, with a half-normal distribution of the farm effects (Table 3). Furthermore, the dummy for policy change was significant. In contrast to model J7 and L8 for Canterbury-Southland (Section 5.3 and Section 6.3) in which the policy change had a neutral effect over production, the impact of the policy change on farm production, given the production technology defined in this model, is negative. As indicated above, it might be concluded that farms in Canterbury-Southland were, on average, 7% less productive after the policy change than before. However, more research is needed in order to disentangle other effects that may be influencing the results reported here[16].

[16] As mentioned above (Section 4.7), this dummy variable may also be capturing effects other than change in the institutional organization of the dairy industry, called for simplicity policy change.

Table 7.6 - Model Y5, data for Canterbury-Southland: maximum likelihood estimates for parameters of the stochastic frontier under VRS (variable returns to scale)

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	3.0702	0.6412
Capital (K2)	β_1	-1.5138	-1.7808 *
Labour (L)	β_2	1.0935	0.7005
Feed (FE)	β_3	1.2215	2.6683 **
Fertiliser (FT)	β_4	0.9874	1.7901 *
Year (Y)	β_t	0.1288	0.8887
$(\text{Year})^2$	β_{tt}	0.0007	0.3237
(K2) x (Y)	β_{1t}	0.0518	2.3463 **
(L) x (Y)	β_{2t}	-0.0438	-2.0711 **
(FE) x (Y)	β_{3t}	0.0148	1.5910
(FT) x (Y)	β_{4t}	-0.0150	-0.8421
$(\text{K2})^2$	β_{11}	-0.2483	-1.2263
(K2) x (L)	β_{12}	0.3682	1.0379
(K2) x (FE)	β_{13}	0.2959	1.7961 *
(K2) x (FT)	β_{14}	0.1323	0.6022
$(\text{L})^2$	β_{22}	0.0823	0.3122
(L) x (FE)	β_{23}	-0.5651	-3.6621 **
(L) x (FT)	β_{24}	-0.3585	-1.4139
$(\text{FE})^2$	β_{33}	0.3220	4.8954 **
(FE) x (FT)	β_{34}	-0.3675	-2.9669 **
$(\text{FT})^2$	β_{44}	0.3029	2.5640 **
Dummy for policy change	*Dpc*	-0.0717	-1.8384 *
Variance parameters			
Sigma	σ^2	0.0122	3.6740 **
Gamma	γ	0.4028	2.4323 **
Technical inefficiency effect	μ_i	Restricted to zero	
Time-varying inefficiency	η	0.2293	6.2736 ***
Log-likelihood function		**121.158**	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Ten out of twenty-one coefficients are significant. Three coefficients of the direct effects are significant: feed at 5% and capital and fertiliser, both at 10%. Three cross terms are significantly different from zero as well as the quadratic terms on feed and fertiliser, confirming that the function is non-linear in some dimensions (Table 7.6). The sign of the coefficient of the time trend, and the square term on time are both positive but not significant. Finally, two interaction terms are significant at 5%: (time *capital) and (time *labour) (Table 7.6).

The value of maximum likelihood estimate for γ is 0.4028 and is significant at 5%, indicating that technical inefficiency in the Canterbury-Southland dairy farms is present but also that noise plays a significant role. Finally, the estimated value of the parameter μ_i is zero, indicating that technical inefficiency effects have a half-normal distribution and the value of maximum likelihood estimate for η is positive, i.e., technical efficiencies increase over time (Table 7.6).

Over the period, labour appears to be the major determinant of dairy production growth, with an average input elasticity of 0.61, followed by fertiliser at 0.21 and feed at 0.06. The marginal output elasticity of capital is negative at -0.12, indicating that there is excess use of capital (Table 7.7). A negative sign for capital output elasticity was reported for Model L8 (Table 6.7, Section 6.3, Chapter 6), whereas a positive capital output elasticity was found for Model J7 (Table 5.7, Section 5.3, Chapter 5).

Average elasticities for capital and feed are significant at 10%. Meanwhile labour and fertiliser elasticities are significant at 5% (Appendix 1, Table A1.3). The negative coefficient on the time-trend variable indicates that the frontier was shifting backwards at an annual rate of 1.68% per annum. The positive sign of the coefficient of the quadratic term on time indicates that the effect is non-linear, but this was small and not significant (Appendix 1, Table A1.3).

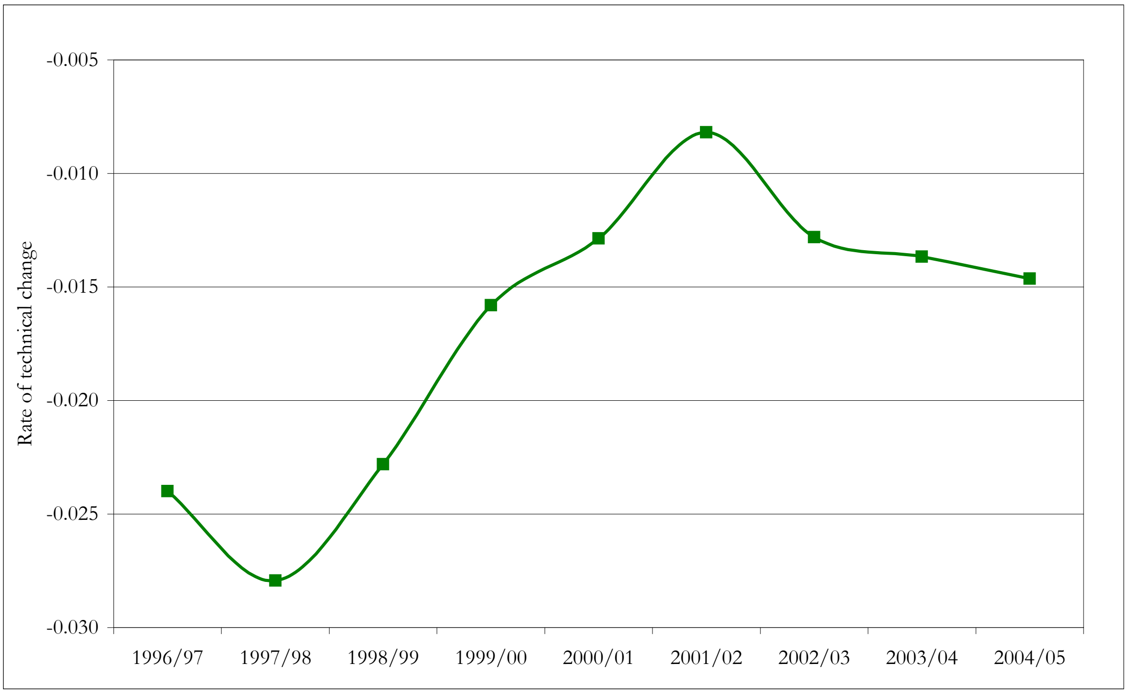
Table 7.7 - Model Y5: elasticity estimates, rate of technical progress and return to scale for Canterbury-Southland

	Output elasticities				Returns to scale	Rate technical change
	Capital	Labour	Feed	Fertilizer		
1996/97	-0.3221	0.7227	0.0536	0.1721	0.6262	-0.0240
1997/98	-0.2811	0.6845	-0.0076	0.2059	0.6017	-0.0279
1998/99	-0.2468	0.6490	0.0227	0.2173	0.6423	-0.0228
1999/00	-0.1402	0.5985	0.1680	0.0950	0.7213	-0.0158
2000/01	-0.1178	0.6057	0.1176	0.2025	0.8081	-0.0129
2001/02	-0.0605	0.6143	0.1268	0.2059	0.8865	-0.0082
2002/03	-0.0279	0.5722	0.0539	0.2314	0.8295	-0.0128
2003/04	0.0071	0.5381	0.0167	0.2668	0.8288	-0.0137
2004/05	0.0746	0.5007	0.0157	0.2691	0.8601	-0.0146
Average	**-0.1206**	**0.6083**	**0.0632**	**0.2081**	**0.7590**	**-0.0168**

Note: average values of output elasticities are estimated at sample mean. The average rate of technical change corresponds to cumulative growth over the period.

These values means that, on average for the period, a 1% increase in labour prompts a 0.61% growth in milk production and a 1% increase in capital provokes a reduction of 0.12% in milk production. The elasticity of scale is 0.76, indicating decreasing returns to scale. Returns to scale increased over time from 0.63 at the beginning of the period to 0.86 by the end of the period. Behind this development is a decline in the elasticity of labour from 0.72 to 0.50, whereas capital output elasticity increased from -0.32 to 0.07. As in Model L8, the negative elasticity of capital at the beginning of the period may be related to significant initial capital investments or the inadequate development of services (Section 6.3, Chapter 6). The marginal output elasticity of feed, which started at 0.05, climbed to 0.17 by season 1999/2000 and then decreased to 0.016 by the last season. Fertiliser elasticity started at 0.17 and after reaching 0.22 two seasons later, decreased to 0.09 by season 1999/2000. The following season it recovered to 0.20 and increased to 0.27 by the last season.

Figure 7.2 - Model Y5: annual rates of technical progress at the frontier for Canterbury-Southland



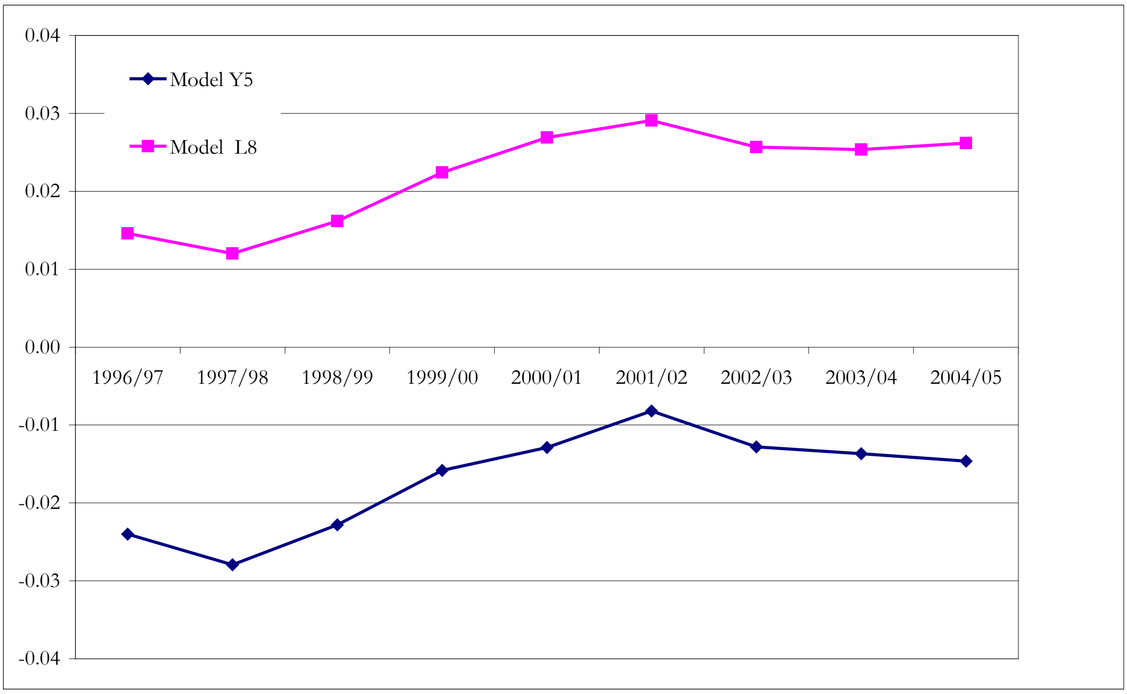
The regional frontier experienced technical regress over the whole period (Figure 7.2). The productivity slowdown was more pronounced at the beginning of the period (-2.40%), it improved gradually up to season 2001/02 where technical regress was at -0.82% and finally declined to -1.28% and further to -1.46% for the last season (Table 7.7 and Figure 7.2). On average over the period, the frontier regressed at 1.68% per annum.

The small increase in the rate of technical regress at the frontier in season 1997/98 may be the result of the drought in the region. Model L8 also captured this. Furthermore, both Model Y5 and Model L8 identified season 2001/02 as the season with the highest rate of technical progress at the frontier (Figure 7.3).

The progressive reduction in the rate of technical regress at the frontier from the beginning of the period up to season 2001/02 may be rooted in the need to increase productivity and hence improve profitability. The downturn over the last three seasons may be the consequence of the high profitability, due to unprecedented higher milk prices, which reduced the incentives to increase productivity. The same was reported for Models L8 (Section 6.3, Chapter 6).

Finally, it can be seen that the annual rates of technical progress at the frontier differ significantly between Model L8 and Model Y5 (Figure 7.3). However, both models identified the high and low in the same seasons. Furthermore, the shape of the curve is the same. Both models differ in two inputs: herd size and area of farm in Model L8 and feed and fertiliser in Model Y5. One possible explanation for the negative values of technical progress in Model Y5 is that both inputs (feed and fertiliser) are measured in value terms. Since prices of both inputs have gone up (in real terms) substantially over the period, the effect of price changes over time might be responsible for the negative value of technical progress.

Figure 7.3 - Model Y5: comparison of the annual rates of technical progress at the frontier for Model L8 and Y5 for Canterbury-Southland



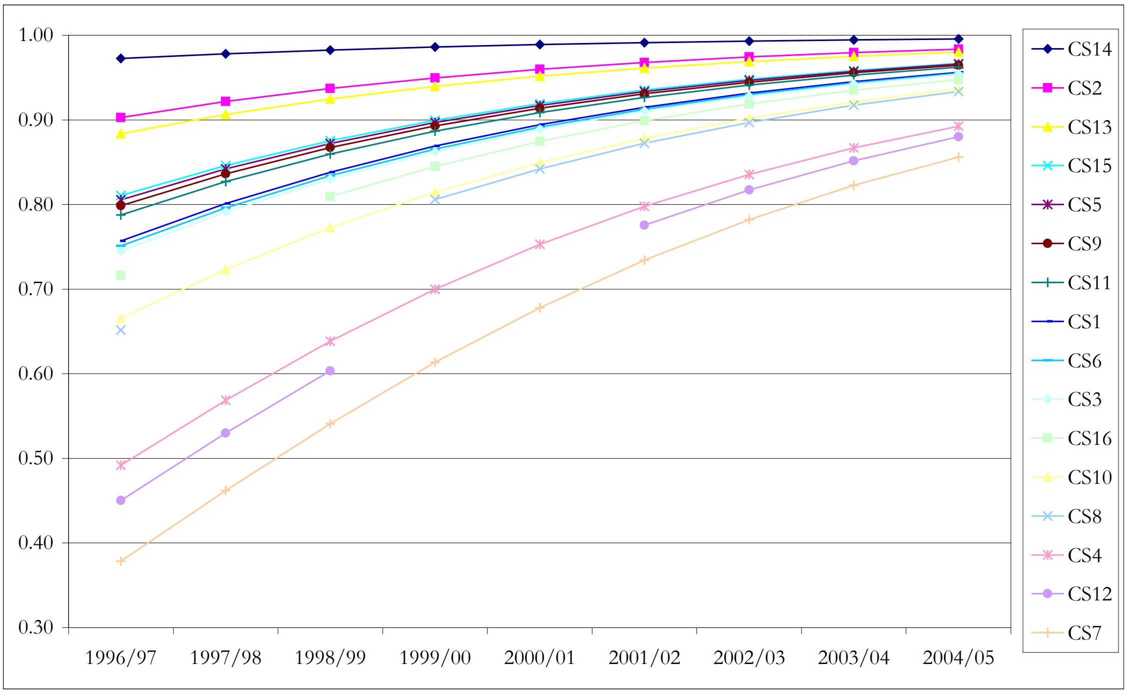
The mean overall technical efficiency is 0.86. This result indicates that the volume of milk produced by the farms in the sample during the period could have been achieved with approximately 14% fewer resources, if all farms had been technically efficient. Technical efficiency averaged 0.72, ranging between 0.97 and 0.38 for season 1996/97. For the last season, mean technical efficiency was 0.94, ranging between 0.99 and 0.85 (Table 8).

Table 7.8 - Model Y5: estimates of technical efficiency by year for Canterbury-Southland

	Mean	Maximum	Minimum	St. deviation
1996/97	0.7230	0.9726	0.3786	0.1638
1997/98	0.7735	0.9781	0.4619	0.1521
1998/99	0.8124	0.9825	0.5410	0.1255
1999/00	0.8551	0.9860	0.6135	0.0950
2000/01	0.8820	0.9889	0.6781	0.0792
2001/02	0.8964	0.9911	0.7342	0.0710
2002/03	0.9162	0.9929	0.7822	0.0582
2003/04	0.9325	0.9944	0.8226	0.0475
2004/05	0.9457	0.9955	0.8561	0.0385

In contrast to farm efficiencies for Waikato-Taranaki, which were constant over the period, the positive sign on the coefficient on the parameter η implies that technical efficiencies increase over time (Figure 7.2). The difference in efficiency between farms was much larger in the earlier years than in the latter years. This indicates that less efficient farms were able to catch up with the frontier.

Figure 7.4 - Model Y5: efficiency scores for the individual farms in Canterbury-Southland*(1)*



(1) Note: In years when particular farmers were not observed, no values of technical efficiency are calculated.

7.4 *Comparison of both regional models*

As indicated previously (Sections 5.4 and 6.4), given that production technologies differ across regions, input elasticities and technical change are not strictly comparable. The most important difference is found to be in the production function that represents the underlying production technology. Whereas a Cobb-Douglas best represented the production technology for Waikato-Taranaki farms, the more flexible translog function was the best representation of the technology applied by farms in Canterbury-Southland. For the Waikato-Taranaki data set estimated input elasticities, returns to scale and technical progress do not differ between farms or over time. Furthermore, technical progress is neutral. In contrast, in the Canterbury-Southland data set, the estimated marginal elasticities, returns to scale and technical progress differ among farms and over time.

For both regions, labour contributes significantly to output growth, as it is the single most important input (Table 7.9). However, the marginal output elasticity of labour is 0.39 for Waikato-Taranaki and 0.60 for Canterbury-Southland. Fertiliser is the second most important input for both regions. Interestingly, the fertiliser output elasticity is 0.25 for Waikato-Taranaki and 0.21 for Canterbury-Southland.

Table 7.9 - Model Y5: comparison of factor input elasticity estimates at sample mean

	Output elasticities				Returns to scale
	Capital	Labour	Feed	Fertiliser	
Waikato-Taranaki	**0.1647**	**0.3912**	**0.2031**	**0.2473**	**1.0063**
Relative contribution (%)	16%	39%	20%	25%	
Canterbury-Southland	**-0.1206**	**0.6083**	**0.0632**	**0.2081**	**0.7590**
Relative contribution (%)	-16%	80%	8%	27%	

Feed is the third most important input. However, feed elasticity for Waikato-Taranaki is at 0.20, almost 3.2 times higher than that estimated for Canterbury-Southland at 0.06. Therefore, a 1% increase in feed use increases milk production by 0.20% in the former region and by only 0.06% in the latter region.

The most important difference is to be found in the value of the marginal output elasticity of capital. Whereas capital output elasticity for Waikato-Taranaki is at 0.16, the value for

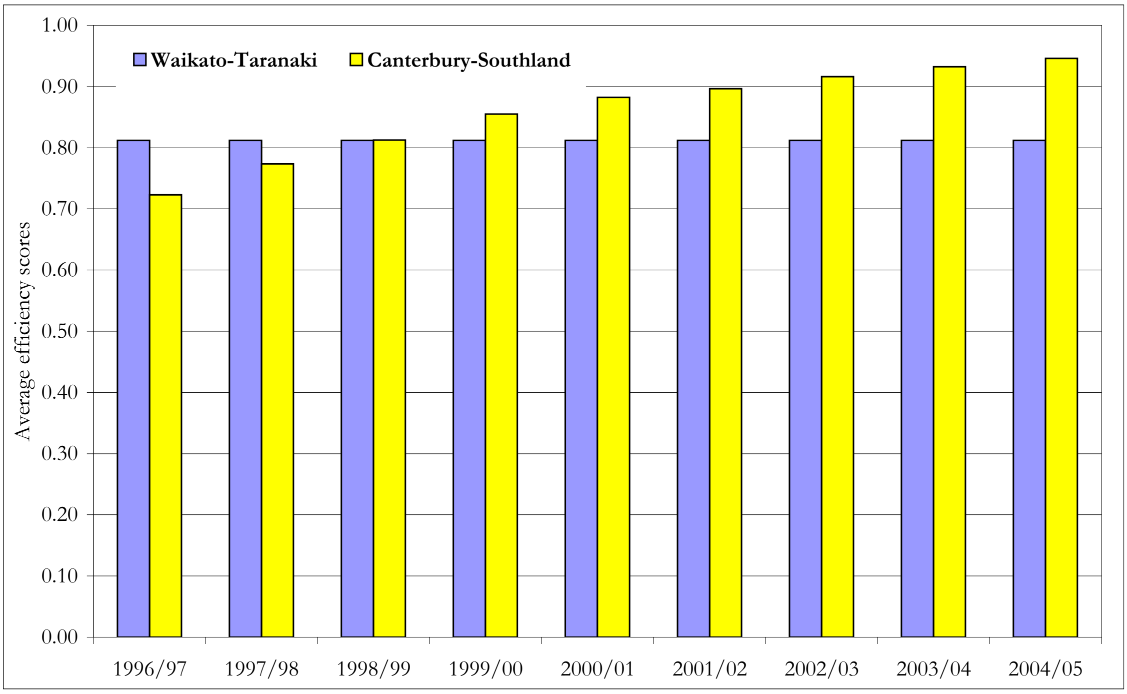
Canterbury-Southland is negative, -0.16, indicating excess input use. As explained above (Sections 5.4 and 6.4), the different sign in the capital output elasticity may be related to differences in the initial levels of development of the infrastructure of services or to the significant initial capital investments in Canterbury-Southland. Finally, Waikato-Taranaki (smaller average farms) is operating at constant returns to scale (RTS), whereas Canterbury-Southland (larger average farms) is operating at decreasing returns, albeit RTS have been increasing over the period (Table 7.7).

Over the period, Canterbury-Southland exhibited technical regress at the frontier (Figure 7.2), whereas Waikato-Taranaki experienced a constant rate of technical progress at the frontier (Table 7.5). In addition, technical change is non-neutral in the former region and Hicks-neutral in the latter.

Another important difference is found in the behaviour of technical efficiency over time. For Waikato-Taranaki, farm technical efficiencies are constant over time, whereas farms in Canterbury-Southland exhibited a progressive improvement (Figure 7.4). Consequently, the dispersion in farm technical efficiencies is constant over time in the former region and decrease in the latter.

Average efficiency for Waikato-Taranaki farms was higher than for Canterbury-Southland farms over the first two seasons of the period, but this was reversed in the last 6 seasons of the period. By the last period, average efficiency for Canterbury-Southland was at 0.94, ranging between 0.85 and 0.99, whereas for Waikato-Taranaki, average efficiency remained at 0.82, ranging between 0.72 and 0.96.

Figure 7.4 - Model Y5: comparison of farm efficiency score between Waikato-Taranaki and Canterbury-Southland



The policy implications of the differences in technical change and in farm efficiencies will be discussed in the next section where the decomposition of TFPG is undertaken.

CHAPTER 8

8 Results for Model K9

8.1 Determination of the preferred functional form

Model K9 was defined in terms of the following factor inputs: cows, labour (hours worked), fertiliser expenditure (deflated by the corresponding price index) and capital (K9, expenditure on repairs and maintenance on vehicles and buildings, plus expenditure on fuel and electricity, plus rates and insurance, administration costs and miscellaneous expenses, deflated by the corresponding price index).

8.1.1 All data pooled across both regions

Empirical results were obtained by using the stochastic frontier production model with time-varying inefficiency effects defined above (Section 4.7). The coefficient on the dummy introduced to capture the effects of the policy change was not significant ($t<2$). This result was confirmed by the LR test.

Given the specifications of the stochastic frontier, various hypotheses were tested to determine the preferred functional form and the distribution of the random variables associated with the existence of technical inefficiency and the residual error term (Table 8.1).

The translog stochastic frontier production model was estimated first. The first null hypothesis that the Cobb-Douglas production function is an adequate representation for the pooled data was accepted. However, the hypothesis of neutral technical change was rejected.

Table 8.1 - Model K9, data for both regions: generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function

Null Hypothesis (*Ho*)	Log-likelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given pooled sample	248.288			
A Cobb-Douglas function is adequate	238.39	19.796	$\chi^2_{.05,\,15} = 25.00$	Accept *Ho*
Technical change is neutral	242.58	11.416	$\chi^2_{.05,\,4} = 9.49$	Reject *Ho*
Traditional average response function is adequate representation of the data (w.r.t. CD) ($\gamma=\mu=\eta=0$)	191.394	93.99	$\chi^2_{.05,\,3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant (w.r.t. CD) $\mu=\eta=0$	231.63	13.52	$\chi^2_{.05,\,2} = 5.99$	Reject *Ho*
Technical inefficiencies have a half-normal distribution (w.r.t. CD) $\mu=0$	235.38	6.02	$\chi^2_{.05,\,1} = 3.84$	Reject *Ho*
Technical inefficiencies are time invariant (w.r.t. CD) $\eta=0$	234.27	8.24	$\chi^2_{.05,\,1} = 3.84$	Reject *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

Given the specifications of the Cobb-Douglas production function, it is evident that the traditional average response function, in which farms are assumed to be fully technical efficient, is not an adequate representation of the data (i.e., the null hypothesis H_0: $\gamma=\mu=\eta=0$ is rejected). Similarly, the null hypotheses, that time-invariant models for farm effects are valid are also rejected (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$ are rejected), indicating that technical efficiency levels varied significantly over time (Table 8.1). Finally, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was also rejected.

The CD stochastic frontier model was estimated with the regional dummy. The value of the log-likelihood function was 242.87. The coefficient of the regional dummy has a value of 0.1082 and it was significantly different from zero at 5% (t-value=3.3657). This result was confirmed by the likelihood-ratio test (LR). Therefore, as for all the other models, there is *a priori* evidence that the stochastic frontier model differs between regions. Furthermore, given the production function defined by the input/output set, Canterbury-Southland sampled farms are, on average, 10.82% more productive than sampled farms in Waikato-Taranaki.

8.1.2 The Waikato-Taranaki sample

The value of the log-likelihood function, for the translog stochastic frontier model with time varying inefficiency effects for Waikato-Taranaki, is 132.41. The coefficient of the dummy introduced to capture the effects of the policy change was not significant. Results of the different hypotheses tested are presented below (Table 8.2). The first null hypothesis that the Cobb-Douglas is an adequate representation of the data was accepted. However, the hypothesis of Hicks-neutral technical change was rejected.

Given the specifications of the Cobb-Douglas production function, the hypothesis that the average response function is an adequate representation of the data was rejected. Conversely, the null hypotheses, that time-invariant models for farm effects are valid, were accepted (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$), indicating that technical efficiency levels did not vary significantly over time. Finally, the hypothesis that the technical inefficiency effects have a half-normal distribution (H_0: $\mu=0$) was also accepted.

Table 8.2 - Model K9, data for Waikato-Taranaki: generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function

Null Hypothesis (*Ho*)	Log-likelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given Waikato-Taranaki sample	132.41			
A Cobb-Douglas function is adequate	125.25	14.32	$\chi^2_{.05,\,15} = 25.00$	Accept *Ho*
Technical change is Hicks-neutral	127.28	10.26	$\chi^2_{.05,\,4} = 9.49$	Reject *Ho*
Traditional average response function is adequate representation of the data (w.r.t. CD) ($\gamma=\mu=\eta=0$)	116.55	7.94	$\chi^2_{.05,\,3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant (w.r.t. CD) $\mu=\eta=0$	125.07	0.36	$\chi^2_{.05,\,2} = 5.99$	Accept *Ho*
Technical inefficiencies have a half-normal distribution (w.r.t. CD) $\mu=0$	125.24	0.02	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*
Technical inefficiencies are time invariant (w.r.t. CD) $\eta=0$	125.15	0.2	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

8.1.3 The Canterbury-Southland sample

Given the specification of the translog stochastic frontier production function with time varying inefficiency effects, the value of the log-likelihood function is 145.23 for Canterbury-Southland sampled farms (Table 8.3). As for the other region, the coefficient of the dummy for policy change was not significantly different from zero by the LR test. The hypotheses that the Cobb-Douglas is an adequate representation and that technical change is Hicks-neutral were both rejected (Table 8.3).

Given the specifications of the translog production function, the hypothesis that the average response function is an adequate representation of the data was rejected. Similarly, the null hypotheses that time-invariant models for farm effects are valid were rejected (i.e., both H_0: $\mu=\eta=0$ and H_0: $\eta=0$), indicating that technical efficiency levels varied significantly over time. Finally, the hypothesis that the technical inefficiency effects had a half-normal distribution (H_0: $\mu=0$) was accepted.

Table 8.3 - Model K9, data for Canterbury-Southland: generalised likelihood-ratio tests of null hypotheses for parameters in the stochastic frontier production function

Null Hypothesis (*Ho*)	Log-likelihood	LR-Test Statistic (λ)	Critical value (0.05)	Decision
Given Canterbury-Southland sample	145.23			
A Cobb-Douglas function is adequate	122.64	45.18	$\chi^2_{.05,\,15} = 25.00$	Reject *Ho*
Technical change is Hicks-neutral	132.25	25.96	$\chi^2_{.05,\,4} = 9.49$	Reject *Ho*
Traditional average response function is adequate representation of the data (w.r.t. TL) ($\gamma=\mu=\eta=0$)	121.36	47.74	$\chi^2_{.05,\,3} = 7.04$	Reject *Ho*
Technical inefficiencies have a half-normal distribution and are time invariant (w.r.t. TL) $\mu=\eta=0$	140.80	8.86	$\chi^2_{.05,\,2} = 5.99$	Reject *Ho*
Technical inefficiencies have a half-normal distribution (w.r.t. TL) $\mu=0$	145.22	0.02	$\chi^2_{.05,\,1} = 3.84$	Accept *Ho*
Technical inefficiencies are time invariant (w.r.t. TL) $\eta=0$	140.87	8.72	$\chi^2_{.05,\,1} = 3.84$	Reject *Ho*

Note: Critical values for the hypotheses tests, except for testing inefficiency effects, are obtained from the appropriate chi-square distribution. The critical value for testing the null hypothesis of no inefficiency effects is taken from Kodde and Palm (1986).

8.1.4 Testing the existence of a common frontier

As was previously mentioned, the value of the coefficient of the regional dummy included in the pooled sample indicates that both regions may not be operating under the same technology. For model K9, the preferred stochastic frontier models are specified below (Table 8.4).

Note that the number of parameters estimated for the pooled sample is 10 (6 parameters in the frontier function (5+1 for the constant), 2 for the variance terms (sigma and gamma), 1 for the scalar η and 1 for the inefficiency effects (u_i)). The number of parameters estimated for Waikato-Taranaki model is 8 (6 parameters in the frontier function (5+1 for the constant), 2 for the variance terms (sigma and gamma)). Finally, the number of parameters estimated for Canterbury-Southland model is 24 (21 parameters in the frontier function (20+1 for the constant), 2 for the variance terms (sigma and gamma), and 1 for the scalar η).

Table 8.4 - Model K9: generalised likelihood-ratio tests of null hypothesis that regions share a common stochastic frontier production function

	Log-likelihood (parameters estimated)	LR-Test Statistic (degrees of freedom)	Critical value (0.05)	Decision
Waikato-Taranaki Cobb-Douglas, $\mu=\eta=0$	125.07 (8)			
Canterbury-Southland TL with non-neutral technical change, $\mu=0$	145.22 (24)			
H_A: $\sum$ [Log-likelihood (WT)]+ [Log-likelihood (CS)]	270.29 (32)			
Ho: Pooled sample Cobb-Douglas	238.39 (10)	-2*(238.39-270.29) = **63.8** df. (32-10=12)	$\chi^2_{.05, 12}$ **=21.0**	Reject *Ho*

The outcome of the test indicates that the two regional stochastic frontiers for dairy farms are not the same, confirming the *a priori* result obtained by using the regional dummy in the pooled stochastic frontier. Therefore, according to the log-likelihood ratio test, farm-level data in the two regions were not generated from a single production frontier or from the same underlying technology. Maximum likelihood parameter estimates for both regions are presented below.

8.2 Waikato-Taranaki

As was mentioned above, the Cobb-Douglas function best represents the underlying technology for the Waikato-Taranaki sampled farms. A similar result was found for Models L8 and Y5. Furthermore, the stochastic frontier has time-invariant inefficiency effects with half-normal distribution (Table 8.5).

Table 8.5 - Model K9, data for Waikato-Taranaki: maximum likelihood estimates for parameters of the stochastic frontier under VRS (variable returns to scale)

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	4.8544	12.1562 ***
Cows (CW)	β_1	0.6694	7.2166 ***
Labour (L)	β_2	0.2447	2.7372 **
Fertilizer (FT)	β_3	0.0833	2.3812 **
Capital (K9)	β_4	0.1392	3.5904 **
Year (Y)	β_t	0.0027	2.0854 **
Variance parameters			
Sigma	σ^2	0.0145	3.4358 **
Gamma	γ	0.5401	3.8086 **
Technical inefficiency effect	μ_i	Restricted to zero	
Time-varying inefficiency	η	Restricted to zero	
Log-likelihood function		**127.07**	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

All the coefficients on the production function are significantly different from zero at 5%. The estimated coefficients are the output elasticities. These are the same across all farms and over time. Furthermore, technical progress is Hicks-neutral. Both test statistics (σ^2 and γ) are significantly different from zero. As indicated above, the estimated coefficients for η and μ_i are zero.

Herd size (number of cows) appears to be the major determinant of dairy production growth, with an average input elasticity of 0.67, followed by labour at 0.24, capital at 0.14 and fertiliser at 0.08. On average for the period, a 1% increase in the number of cows results in a growth of 0.67% in milk production *ceteris paribus*. Similarly, the outcome of a 1% increase in capital is an expansion of 0.14% in milk production. The elasticity of scale is found to be 1.1365, indicating increasing returns to scale. Increasing returns to scale have been found for Model L8, whereas constant returns were revealed for Model J7 and Model Y5.

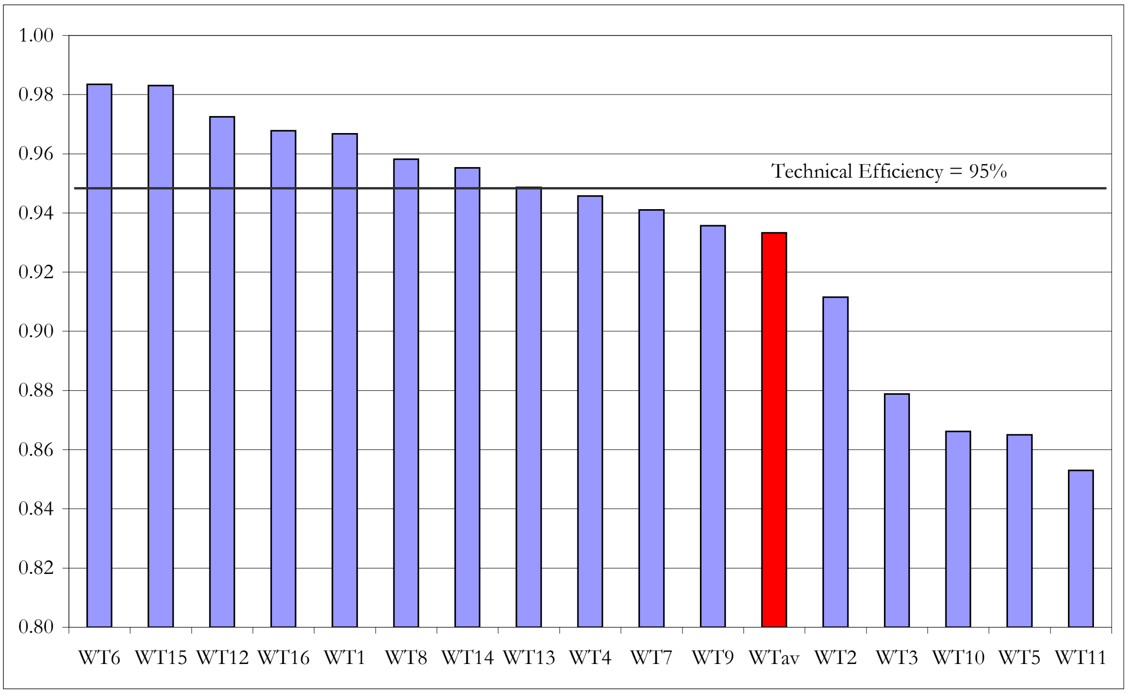
The frontier was shifting upwards (technical progress) at a constant rate. The rate of exogenous technical progress is found to be increasing productivity by 0.27% per annum. This value is slightly less than the one found for Model J7 (Section 5.2, Chapter 5) and for Model Y5 (Section 7.2, Chapter 7), where the frontier was shifting at 0.47% and 0.41% per annum respectively. Meanwhile, for Model L8 (Section 6.2, Chapter 6), no technical progress was found (technical progress was negative but not significant).

Given that η=0, there is no change in technical efficiency over time. As for Model Y5, this result was not expected, given the sluggish rate of technical progress. However, as indicated above (Section 7.2), this may be the result of the restriction imposed by using the time-varying inefficiency model.

The mean overall technical efficiency is 0.933, ranging between 0.853 and 0.983 (Figure 8.1). This result indicates that the volume of milk produced by the farms in the sample during the period could have been achieved with approximately 6.7% fewer resources, if all farms had been technically efficient.

It can also be seen that the dispersion in farm technical efficiency is low (the coefficient of variation is 4.7%). Furthermore, seven farms had a technical efficiency higher than 0.95, while four had efficiency estimates lower than 0.90 (Figure 8.1). Average technical efficiency and its range are similar to those reported for Model L8 (Section 6.2, Chapter 6). As for Model L8, this indicates that the technology defined by this input/output set is being used adequately. In turn, the fact that technical progress at the frontier was zero and that farm efficiency scores are high (i.e., technology is being applied adequately) leads to the conclusion that farms in the sample need a new technological paradigm to be able to increase productivity.

Figure 8.1 - Model K9: efficiency scores for the individual farms in Waikato-Taranaki



8.3 Canterbury-Southland

The preferred specification for the Canterbury-Southland region is a translog stochastic frontier with non-neutral technical change time-varying inefficiency effects with half-normal distribution (Table 8.4). As for Model J7 and Model L8, and in contrast to Model Y5 (Section 7.3, Chapter 7), the impact of the policy change on the production technology defined in this model is neutral. That is, the LR test indicates that the coefficient of the dummy variable, incorporated to capture the policy change, was not different from zero.

Many individual parameter estimates are non-significant. although the overall explanatory power of the equation is acceptable (σ^2 and γ are both significantly different from zero). Furthermore, the individual estimates of elasticity of output with respect to labour are negative for some years (Table 8.9). These suggest that the model suffers from multicollinearity. The correlations between herd size, fertiliser and capital are high. Even though multicollinearity is not a concern for the measurement of technical efficiency (Hallam and Machado, 1996 and Jaforullah and Devlin, 1996) and hence the estimation of technical efficiency change, it may be a problem for the assessment of technical progress because this is estimated using the parameter estimates.

The coefficient of the time trend is significant at 10%, but not the quadratic term on time. Furthermore, three cross terms of time with inputs are significant at 5%. Finally, the coefficient on the quadratic term of capital is significant (Table 8.8). Given that most of the coefficients on time were significant, whereas most of the cross terms were not significant, the simplified translog function (the cross terms between inputs were jointly zero) was tested but rejected at 5%.

Given the specifications of the general frontier, the stochastic frontier has time varying inefficiency effects (the scalar η is significantly different from zero) with half-normal distribution (μ_i=0). The value of maximum likelihood estimate for γ is 0.49 and is significant at 5%, indicating that technical inefficiency in the Canterbury-Southland sampled dairy farms is present but also that noise plays a significant role.

Table 8.8 - Model K9: maximum likelihood estimates for parameters of the stochastic frontier production function for Canterbury-Southland

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	-0.3065	-0.0807
Cows (CW)	β_1	-3.1137	-1.7745
Labour (L)	β_2	4.7116	2.2833 **
Fertiliser (FT)	β_3	0.5801	0.7995
Capital (K9)	β_4	-1.0972	-1.5537
Year (Y)	β_t	-0.0392	-1.9660 **
$(\text{Year})^2$	β_{tt}	-0.0025	-1.5779
(CW) x (Y)	β_{1t}	-0.0677	-1.8059 *
(L) x (Y)	β_{2t}	0.0155	0.5112
(FT) x (Y)	β_{3t}	0.0457	3.3195 **
(K9) x (Y)	β_{4t}	0.0322	2.4836 **
$(\text{CW})^2$	β_{11}	0.4270	0.4851
(CW) x (L)	β_{12}	0.2684	0.1757
(CW) x (FT)	β_{13}	-0.3917	-1.1325
(CW) x (K9)	β_{14}	0.5883	1.2603
$(\text{L})^2$	β_{22}	-0.7177	-1.0179
(L) x (FT)	β_{23}	0.1071	0.2975
(L) x (K9)	β_{24}	0.1990	0.4638
$(\text{FT})^2$	β_{33}	0.0759	0.6096
(FT) x (K9)	β_{34}	-0.1669	-0.8224
$(\text{K9})^2$	β_{44}	-0.2941	-2.4163 **
Variance parameters			
Sigma	σ^2	0.0107	2.8941 **
Gamma	γ	0.4902	2.7427 **
Technical inefficiency effect	μ_i	Restricted to zero	
Time varying inefficiency	η	0.1476	2.7810 **
Log-likelihood function		**145.22**	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Over the period, number of cows appears to be the major determinant of dairy production growth, with an average input elasticity of 0.98, followed by labour at 0.03. The marginal output elasticity of capital is negative at -0.07 (Table 8.9). A negative capital elasticity, albeit on a different measure of capital, was reported for Model L8 (Table 6.7, Section 6.3) and for Model Y5 (Table 7.7, Section 7.3). The negative elasticity of fertilizer is unexpected, as is the low value of labour elasticity, suggesting multicollinearity problems discussed above.

Average elasticity for herd size was significant at 5%, while capital and fertilizer elasticities were significant at 10% and labour elastictity was not significant. The coefficient on the time-trend variable indicates that the frontier was shifting upwards at an annual rate of 1.57% per annum. The coefficient of the quadratic term on time is small and negative but is not significantly different from zero (Appendix 1, Table A1.4). On average for the period, a 1% increase in the number of cows resulted in a growth of 0.98% in milk production. Similarly, a 1% increase in capital is associated with a reduction of 0.07% in milk production.

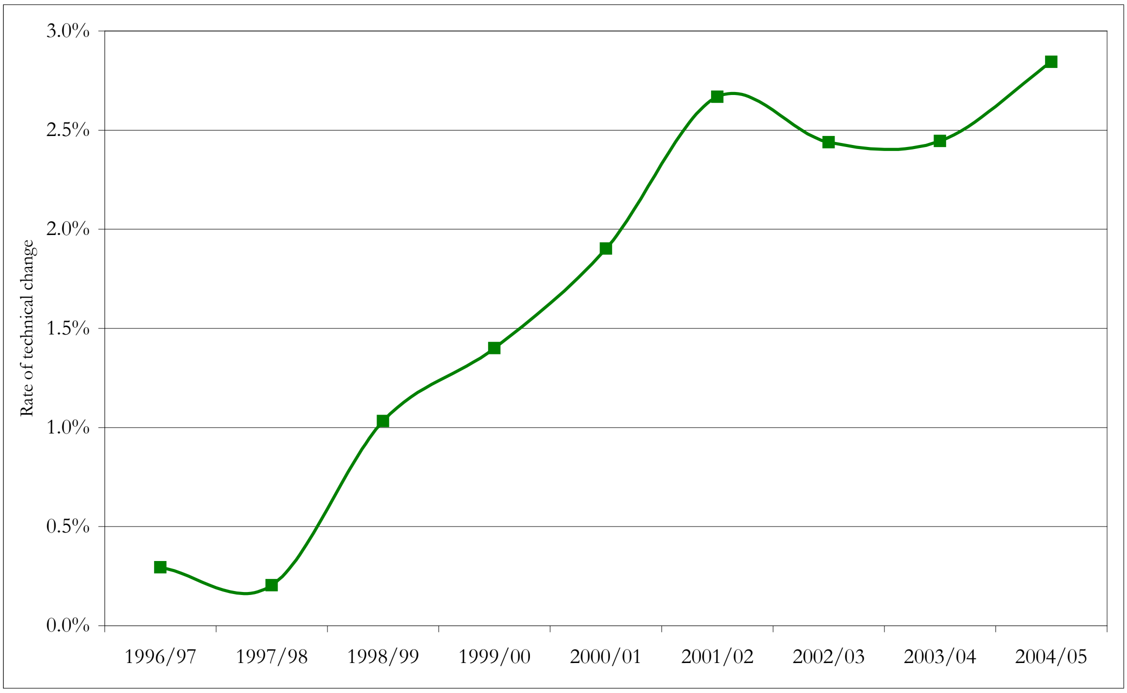
Table 8.9 - Model K9: elasticity estimates, rate of technical progress and return to scale for Canterbury-Southland

	Output elasticities				Returns to scale	Rate technical change
	Cows	Labour	Fertilizer	Capital		
1996/97	1.1488	0.0624	-0.2369	-0.2237	0.7506	0.0029
1997/98	1.1122	0.0239	-0.1926	-0.1833	0.7601	0.0020
1998/99	1.0762	0.0822	-0.1502	-0.1572	0.8509	0.0103
1999/00	0.9755	0.0739	-0.1289	-0.1261	0.7944	0.0140
2000/01	1.0060	0.0507	-0.0726	-0.0807	0.9034	0.0190
2001/02	1.0010	-0.0013	-0.0483	-0.0238	0.9276	0.0267
2002/03	0.9243	-0.0074	-0.0087	0.0131	0.9213	0.0244
2003/04	0.8471	-0.0154	0.0330	0.0506	0.9154	0.0245
2004/05	0.7900	-0.0258	0.0795	0.0881	0.9319	0.0284
Average	**0.9843**	**0.0297**	**-0.0782**	**-0.0687**	**0.8670**	**0.0157**

Note: Average values of output elasticities are estimated at sample mean. The average rate of technical change corresponds to cumulative growth over the period.

The elasticity of scale was 0.87, indicating decreasing returns to scale. Returns to scale have been increasing over time from 0.75 at the beginning of the period to 0.93 by the end. Behind this development is the decline in the marginal elasticity of herd size from 1.15 to 0.79, whereas the marginal output elasticities of fertilizer and capital increased from -0.24 to 0.08 and from -0.22 to 0.09 respectively. Meanwhile, the marginal elasticity of labour started at 0.06 and declined to -0.026 (Table 8.9).

Figure 8.3 - Model K9: annual rate of technical progress at the frontier for Canterbury-Southland



The regional frontier experienced technical progress over the whole period, more slowly at the beginning of the period (0.29%), but then improving gradually up to season 2001/02, where technical progress was at 2.67%. It then suffered a small deceleration before finally increasing to 2.84% for the last season (Table 8.9 and Figure 8.3). On average over the period, the frontier was progressing at 1.57% per annum, as indicated above.

The small decline in the rate of technical progress at the frontier in season 1997/98 may have been associated with the drought experienced in Canterbury[17]. Model L8 and Model Y5 also captured this. Both Model Y5 and Model L8 identified season 2001/02 as the season with the highest rate of technical progress at the frontier. However, for Model K9, the highest rate of technical progress was found for the last season. Nevertheless, this model also captured the high rate of technical progress for season 2001/02 (Figure 8.3).

The progressive increase in the rate of technical progress at the frontier from the beginning of the period up to season 2001/02 may be rooted in the need to increase productivity and hence improve profitability. The small decline in the rate of technical progress for the next

[17] There was a severe drought in Canterbury in 1997–99. Regional economic impacts of the 1997–1999 Canterbury drought, MAF 2000.

two seasons may be the consequence of the high profitability, due to unprecedented higher milk prices, which reduced the incentives to increase productivity. The same was reported for Models L8 (Section 6.3, Chapter 6).

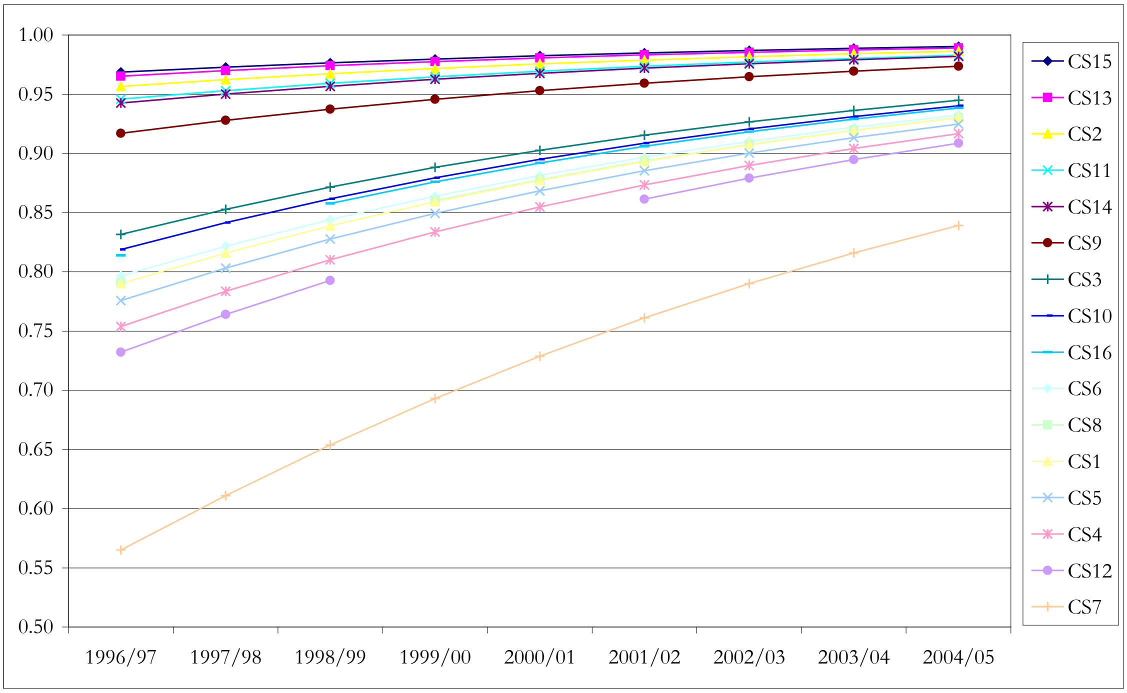
The mean overall technical efficiency is 90%. This result indicates that the volume of milk produced by the farms in the sample during the period could have been achieved with approximately 10% fewer resources, provided all farms were technically efficient. The positive sign on the coefficient of the parameter η implies that technical efficiencies increase over time (Figure 8.4). For the first season, average technical efficiency was 0.83, ranging between 0.97 and 0.56. Meanwhile, for the last season, average technical efficiency climbed to 0.94, ranging between 0.99 and 0.84 (Table 8.10).

Table 8.10 - Model K9: estimates of technical efficiency by year for Canterbury-Southland

	Mean	Maximum	Minimum	St. deviation
1996/97	0.8353	0.9687	0.5651	0.1095
1997/98	0.8593	0.9729	0.6111	0.1041
1998/99	0.8753	0.9766	0.6538	0.0891
1999/00	0.8936	0.9797	0.6930	0.0768
2000/01	0.9071	0.9825	0.7287	0.0677
2001/02	0.9154	0.9848	0.7610	0.0593
2002/03	0.9264	0.9869	0.7901	0.0520
2003/04	0.9359	0.9887	0.8160	0.0455
2004/05	0.9444	0.9902	0.8391	0.0398

The dispersion in technical efficiencies of dairy farmers was considerable at the beginning but converged over time (the standard deviation fell from 0.11 to 0.04 over the period) (Figure 8.4 and Table 8.10). Therefore, even though the region exhibited technical progress at the frontier, less efficient farms were able to catch up with the frontier farms.

Figure 8.4 - Model K9: efficiency scores for individual farms in Canterbury-Southland*(1)*



(1) Note: In years when particular farmers were not observed, no values of technical efficiency are calculated.

8.4 Comparison of both regional models

As indicated previously, given that production technologies differ across regions, input elasticities and technical change are not strictly comparable. As for Model J7, Model L8 and Model Y5, a Cobb-Douglas best represented the underlying production technology for farms in Waikato-Taranaki, whereas the more flexible translog function was used to represent the technology for farms inCanterbury-Southland.

For both regions, herd size contributed significantly to output growth as the single most important input (Table 8.13). However, the marginal output elasticity of herd size was higher in the southern region: 0.66 for Waikato-Taranaki and 0.98 for Canterbury-Southland. Meanwhile, the marginal output elasticity of labour is different across regions: 0.24 for Waikato-Taranaki and 0.03 for Canterbury-Southland.

The most important difference is to be found in the value of the marginal output elasticities of fertiliser and capital. Capital output elasticity for Waikato-Taranaki was 0.14, whereas Canterbury-Southland exhibited a significant input congestion with an elasticity of

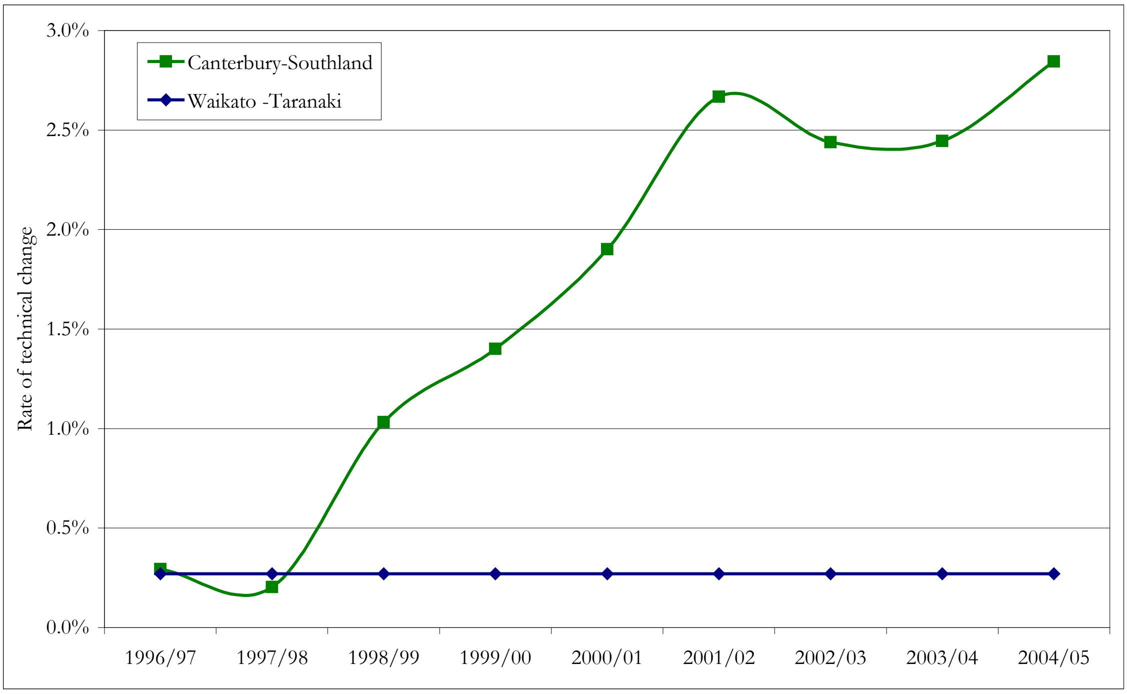
-0.07. Finally, fertiliser output elasticity was 0.08 and -0.08 for Waikato-Taranaki and Canterbury-Southland respectively. As explained above (Sections 5.4, 6.4 and 7.4), the different sign in the capital output elasticity may be related to the degree of development of the infrastructure of services and to the significant investments incurred by farms located in the southern region. Finally, farms in Waikato-Taranaki were operating at increasing returns to scale. Conversely, Canterbury-Southland farms were operating at decreasing returns to scale. However, returns to scale have continuously increased over the period considered (Table 8.9).

Table 8.13 - Comparison of factor input elasticity estimates at sample mean

	Output elasticities				Returns to scale
	Cows	Labour	Fertilizer	Capital	
Waikato-Taranaki	**0.6694**	**0.2447**	**0.0833**	**0.1392**	**1.1366**
Relative contribution (%)	59%	22%	7%	12%	100%
Canterbury-Southland	**0.9843**	**0.0297**	**-0.0782**	**-0.0687**	**0.8670**
Relative contribution (%)	114%	3%	-9%	-8%	100%

Both regions exhibited technical progress at the frontier. However, for farms in Canterbury-Southland, the rate of technical progress increased over the period, whereas sampled farms in Waikato-Taranaki experienced a constant rate of technical progress (Figure 8.7).

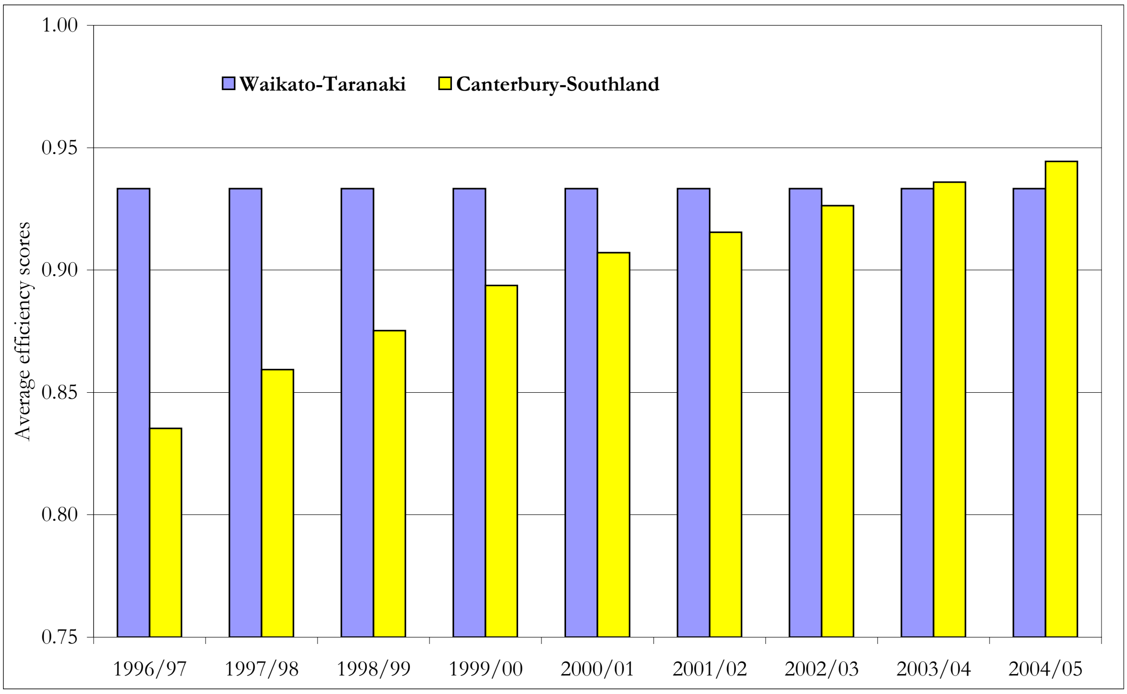
Figure 8.7 - Model K9: annual rate of technical progress at the frontier for Waikato-Taranaki and Canterbury-Southland



The other relevant difference is found in the behaviour of technical efficiency over time. For Waikato-Taranaki, farm technical efficiencies are constant over time. Meanwhile, technical efficiency for farms in Canterbury-Southland exhibited a progressive improvement (Figure 8.8). Consequently, the dispersion in farm technical efficiencies is constant over time in the former region and decreases in the latter.

Average efficiency for Waikato-Taranaki farms was higher than for Canterbury-Southland farms over most of the period. By the last season, average efficiency for Canterbury-Southland was at 0.94, ranging between 0.85 and 0.99, whereas for Waikato-Taranaki, average efficiency remained at 0.93, ranging between 0.85 and 0.98.

Figure 8.8 - Model K9: comparison of farm efficiency score between Waikato-Taranaki and Canterbury-Southland



CHAPTER 9

9 Total Factor Productivity Decomposition

9.1 Introduction

In this chapter, TFP is decomposed into changes in the frontier (technical progress, TP) and changes in efficiency (technical efficiency change, TEC) for each model and region. As mentioned in the introductory chapter, the primary objective was to ascertain whether TFP estimates, and its components, are robust to the selection of the input/output set. This was studied in this thesis by comparing the estimates of TFP derived by four models that differed in their inputs, for farms in two regions.

A stochastic frontier approach was used to construct indices of TFPG. A translog stochastic production function was specified and estimated for each region.
In the extensive form:

$$\begin{aligned}\ln Y_{it} &= \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_t t + \beta_{tt} t^2 + \beta_{1t} x_1 t + \beta_{2t} x_2 t \\ &+ \beta_{3t} x_3 t + \beta_{4t} x_4 t + \beta_{11} x_1 x_1 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{14} x_1 x_4 + \beta_{22} x_2 x_2 \\ &+ \beta_{23} x_2 x_3 + \beta_{24} x_2 x_4 + \beta_{33} x_3 x_3 + \beta_{34} x_3 x_4 + \beta_{44} x_4 x_4 + DPch + V_{it} - U_{it}\end{aligned} \quad (1)$$

where:
Y denotes output
x_1 to x_4 represent the natural log of the factor input. The stochastic frontier model (SFM) was estimated for different combinations of factors inputs (Chapter 4, Table 4.3)
x_5 is the year of observation, where x_5= 1 to 9 for the seasons 1996/97, 1997/98, 1998/99, 1999/2000, 2000/01, 2001/02, 2002/03, 2003/04 and 2004/05 respectively;
DPch is a dummy variable equal to 0 for season 1996/97 to season 2000/01 and equal to 1 for the latter years.
V_{it} and U_{it} are the random variables defined above (Chapter 4, section 4.4)

As explained above, the Malmquist TFP index is best measured relative to a constant return to scale (CRS) technology, as TFP indices obtained through a VRS technology may not properly account for the influence of scale (Chapter 4). The results reported in the previous chapters (5, 6, 7 and 8) were estimated using a variable return to scale (VRS) technology. Estimates of the parameters associated with these models using a CRS technology are reported in Appendix 2. The parameters estimated using the CRS technology were used to calculate the Malmquist TFP index reported in this chapter.

Indices of technical change and technical efficiency change were calculated for each farm between consecutive years using the procedure described in the methodology (Chapter 4, section 4.2) for each of the models estimated in the previous chapters. Following Coelli, Rao and Battese (1998), these indices were aggregated using geometric means and the resultant indices were converted into cumulative indices. Therefore, TEC, TP and TFP indices reported below correspond to the regional level. Farm-level estimates for technical efficiency, technical efficiency change, technical progress and total factor productivity at each time period and for each model are reported in Appendix 3.

9.2 Waikato-Taranaki

Before undertaking the decomposition of TFP, a descriptive summary of the four models estimated for Waikato-Taranaki is introduced.

Table 9.1 - Waikato-Taranaki: summary of the four models

	Functional form	Technical progress (at the frontier)	Technical efficiency Mean (range)
Model J7	Cobb-Douglas	Hicks-neutral 0.67% per annum	Time-invariant 0.87 (0.75-0.98)
Model L8	Cobb-Douglas	Hicks-neutral 0.32% per annum	Time-invariant 0.94 (0.87-0.98)
Model Y5	Cobb-Douglas	Hicks-neutral 0.39% per annum	Time-invariant 0.81 (0.72-0.96)
Model K9	Cobb-Douglas	Hicks-neutral 0.56% per annum	Time-invariant 0.93 (0.85-0.98)

9.2.1 Technical efficiency change, as estimated by the four models

Farm technical efficiency estimated by all models (Model J7, Model L8, Model Y5 and Model K9) showed no changes over the period (technical efficiency was time-invariant, η=0). This implies that for all farms, their respective distance from the production frontier remained the same over the whole period. Therefore, the cumulative indices of technical efficiency change equal 1 over the whole period for all these models (Table 9.2).

Table 9.2 - Cumulative indices of technical efficiency change for Waikato-Taranaki region, estimated by the four models

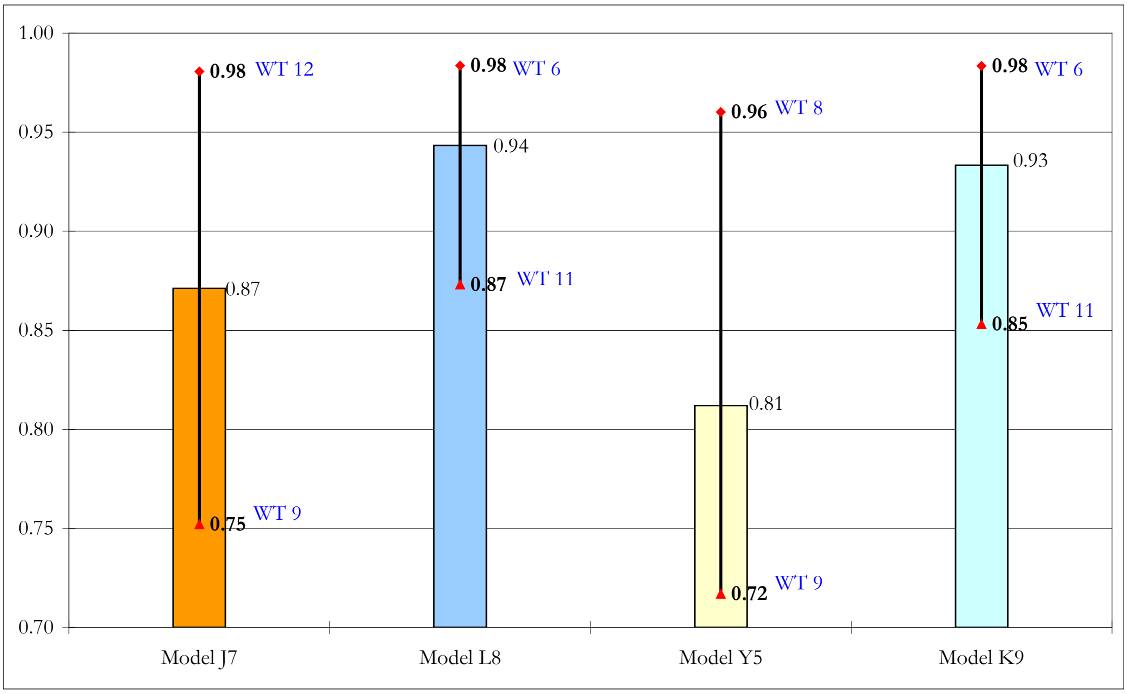
	Model J7	Model L8	Model Y5	Model K9
1996/97 to 2004/05	1.0000	1.0000	1.0000	1.0000
Cumulative (%)	**0.0%**	**0.0%**	**0.0%**	**0.0%**

Note: 1.000= no change

The average efficiency over the period, which is a measure of the structural efficiency (Kumbhakar and Hjalmarsson, 1992), was at 87% for Model J7, 94% for Model L8, 81% for Model Y5 and 93% for Model K9, indicating that on average over the period, milk production could have been increased by 13%, 6%, 19% and 7% respectively, given the level of resources used provided all units were technical efficient (Table 9.1).

Mean technical efficiency and its range are similar for Model L8 and Model K9, but these values differ significantly from the results of Model Y5 and Model J7 (Figure 9.1). Interestingly, farms WT6 and WT11 ranked highest and lowest respectively in technical efficiency for Model L8 and Model K9. For Model J7 and Model Y5, farm WT12 and farm WT8 ranked highest respectively. Meanwhile, farm WT9 ranked lowest for both models (Figure 9.1).

Figure 9.1 - Waikato-Taranaki: average efficiency scores and its range of the four models



The average estimates of farm efficiency for all the models proposed are reported below (Table 9.3). All four models estimated for Waikato-Taranaki revealed that technical efficiency was time-invariant (Table 9.1). The adjacent column (in grey) shows the farm's rank using each efficiency estimate. As shown (Table 9.3), there is a difference in the magnitude of the efficiency estimates. However, the Pearson correlation coefficient shows a significant correlation in efficiency scores among alternative models. For example, efficiency estimates from models L8 and K9 have a Pearson correlation coefficient of 0.885

(significant at 1%) while those from models J7 and Y5 have a Pearson correlation coefficient of 0.843. All the other Pearson correlation coefficients are also significant.

Table 9.3 - Farm efficiency estimates and correlation of farm efficiency estimates given the alternative input/output sets for Waikato-Taranaki

	Model							
	L8		J7		Y5		K9	
Farm	Av efficiency	**Rank**	Av efficiency	**Rank**	Av efficiency	**Rank**	Av efficiency	**Rank**
WT1	0,968	**5**	0,847	**10**	0,774	**10**	0,941	**4**
WT2	0,938	**11**	0,844	**11**	0,805	**7**	0,902	**10**
WT3	0,905	**13**	0,758	**15**	0,730	**15**	0,853	**13**
WT4	0,962	**7**	0,759	**14**	0,759	**13**	0,929	**6**
WT5	0,892	**14**	0,875	**9**	0,792	**9**	0,801	**15**
WT6	0,984	**1**	0,947	**4**	0,877	**3**	0,986	**1**
WT7	0,933	**12**	0,903	**7**	0,866	**4**	0,896	**11**
WT8	0,977	**3**	0,954	**3**	0,960	**1**	0,907	**7**
WT9	0,951	**9**	0,752	**16**	0,717	**16**	0,855	**12**
WT10	0,891	**15**	0,792	**13**	0,760	**12**	0,812	**14**
WT11	0,873	**16**	0,820	**12**	0,770	**11**	0,780	**16**
WT12	0,960	**8**	0,981	**1**	0,950	**2**	0,957	**3**
WT13	0,942	**10**	0,885	**8**	0,748	**14**	0,934	**5**
WT14	0,974	**4**	0,911	**6**	0,796	**8**	0,903	**9**
WT15	0,978	**2**	0,980	**2**	0,866	**5**	0,982	**2**
WT16	0,964	**6**	0,930	**5**	0,821	**6**	0,904	**8**
Pearson's correlation coefficients								
L8	1		0,531		0,472		0,885*	
J7			1		0,843*		0,578	
Y5					1		0,487	
K9							1	
Spearman's rank order correlation								
L8		**1**		**0,571**		**0,503**		**0,903***
J7				**1**		**0,647**		**0,703***
Y5						**1**		**0,594**
K9								**1**

* significant at 1% level

The Spearman rank correlation[18] coefficient was administered to determine how close the rankings of farms are among the different models (Table 9.3). The values of the Spearman

[18] This test has been used previously by Ahmad and Bravo-Ureta (1996), Bravo-Ureta and Rieger (1990) and Mbaga et al. (2003) to examine the rankings of technical efficiency estimates.

rank correlation coefficient ranged from moderate (between Model L8 and Model Y5) to high (between Model L8 and Model K9) and all were significant. Therefore, the hypothesis of equal rankings of farm technical efficiency could not be rejected for any of the comparisons (Table 9.3). These results suggest that both the precise value of technical efficiency and the farm ranking are not very dependent on the choice of the input/output set. However, more research in needed with a larger database, as correlations are weak.

9.2.2 Technical progress, as estimated by the four models

Technical progress increased by 2.6% for Model L8, 3.2% for Model Y5, 4.5% for Model K9 and 5.5% for Model J7 over the nine-year period (Table 9.4). For all models estimated for Waikato-Taranaki, the preferred functional form was a CD, hence, technical progress was Hicks-neutral and the rate of change was constant over the years (Table 9.1). The annual rate of technical progress over the period was at 0.32%, 0.39%, 0.56% and 0.67% per annum for Models L8, Y5, K9 and J7 respectively[19] (Tables A2.1; A2.3; A2.5; A2.7 from Appendix 2). The Cobb-Douglas function was used to represent the underlying production technology in all of the models specified for Waikato-Taranaki (Sections 5.2, 6.2, 7.2 and 8.2).

Table 9.4 - Cumulative indices of change in technical progress for Waikato-Taranaki region, estimated by the four models

	Model J7	Model L8	Model Y5	Model K9
1996/97	1,000	1,000	1,000	1,000
1997/98	1,007	1,003	1,004	1,006
1998/99	1,013	1,006	1,008	1,011
1999/00	1,020	1,010	1,012	1,017
2000/01	1,027	1,013	1,016	1,022
2001/02	1,034	1,016	1,020	1,028
2002/03	1,041	1,019	1,024	1,034
2003/04	1,048	1,023	1,028	1,040
2004/05	1,055	1,026	1,032	1,045
Cumulative (%)	**5.5%**	**2.6%**	**3.2%**	**4.5%**

Annual rates of technical progress for Waikato-Taranaki are very modest for all of the input/output sets proposed, but were highest for Model J7. Because the annual rate of technical progress is constant for all the models, differences among the models increased over the years when the cumulative index of technical progress is estimated (Table 9.4).

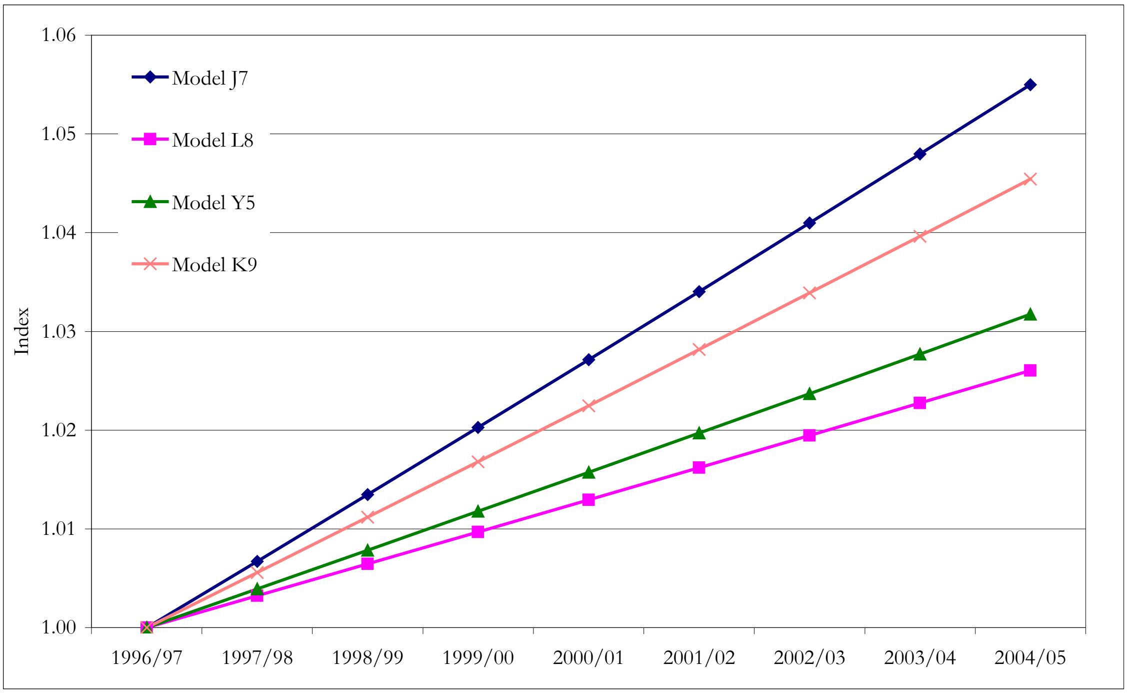
Use of the Cobb-Douglas production function implies that technical change is identical across farms (all the cross terms are equal to zero). Therefore, even though technical progress at the frontier (and also for all farms) was different between alternative input/output sets, it was impossible to statistically assess the result.

9.2.3 Total Factor Productivity change, as estimated by the four models

When the amount of technical progress is combined with the technical efficiency change, a net increase in TFP is obtained for all models. Overall, the cumulative increases in TFP were 5.5% for Model J7, 2.6% for Model L8, 3.2% for Model Y5 and 4.5% for Model K9, over the nine-year period (Figure 9.2).

[19] The parameters estimated using the CRS technology were used to calculate the Malmquist TFP index reported in this chapter.

Figure 9.2 - Cumulative indices of TFP change for Waikato-Taranaki region, estimated by the four models



Average TFP change over the period was at 0.59%, 0.29%, 0.35% and 0.49% per annum for Models J7, L8, Y5 and K9 respectively (Table 9.5), which is much smaller than the target of 4% annual increase. Furthermore, for all models considered, technical progress is the sole contributor to TFP change, as technical efficiency change is nil (Table 9.5).

Table 9.5 - Average annual change in TFP and its sources by model for Waikato-Taranaki

	TFP	TEC	TP
Model J7	0.59%	0%	0.59%
Model L8	0.29%	0%	0.29%
Model Y5	0.35%	0%	0.35%
Model K9	0.49%	0%	0.49%

Even though the time-varying inefficiency model (Chapter 4) used in this research is restrictive because it assumed that all farms follow a common trend, the absence of any change in technical efficiency was surprising, given the sluggish rate of technical progress estimated by all the four input/output sets. However, the results are consistent: all models exhibited a small rate of technical progress and no technical efficiency change.

Model L8 (defined by herd size, labour, capital(K1) and area of farm) and Model K9 (defined by herd size, labour, capital(K9) and fertiliser) probably best represent the traditional technology applied in NZ, and particularly in Waikato-Taranaki, reliant on the intensive use of grass. Given that this technology has been used for many years, most farmers are acquainted with it and hence their efficiency is high. Moreover, both models identify the same two farms to have minimum and maximum efficiency (Table 9.3). The comparison of the physical, biological and financial details of these farms are beyond the scope of this thesis.

Model Y5 (defined by capital (K1), labour, feed and fertiliser) can be an adequate representation of the new technology, where feed (forage or supplements) is brought from outside the farm system. The mastery of this technology is limited, resulting in the lowest value of average efficiency (0.812) and a distribution skewed towards low levels of technical efficiency (Table 9.6).

In turn, Model J7 (defined by area of farm, labour, capital1 and intermediate input[20]) is intermediate between the other two representations. Average technical efficiency is high (closer to the value exhibited by the Models L8 and K9 representing the traditional technology) but, in contrast to Models L8 and K9, the dispersion of technical efficiencies is similar to Model Y5 (Table 9.6).

[20] Mostly comprised of feed and fertiliser expenditure

Table 9.6 - Descriptive statistics of technical efficiency over the period for Waikato-Taranaki, estimated by four models

Technical efficiency range (%)	Model J7		Model L8		Model Y5		Model K9	
	Nº farms	Range average	Nº farms	Range average	Nº farms	Range average	Nº farms	Range average
> 95	3	0.97	5	0.97	2	0.96	3	0.97
90/95	4	0.92	6	0.93			7	0.92
85/90	2	0.88	2	0.87	3	0.87	3	0.87
80/85	3	0.84	3	0.82	2	0.81	2	0.81
75/80	4	0.77			6	0.78	1	0.78
70/75					3	0.73		
Average		0.871		0.913		0.812		0.894
Maximum		0.981		0.989		0.960		0.986
Minimum		0.752		0.810		0.717		0.780
Coef. of variation		9.0%		6.0%		9.0%		6.9%

As a general remark, results for all models seem to indicate that TFP change is very modest, at least relative to the target of 4% annual increase proposed by the industry plan. As mentioned above, for all the models, technical progress is the sole contributor to TFP change (Table 9.5). Furthermore, the amount of technical progress is small for all models (Table 9.5), indicating that the adoption of new technology is taking place very slowly. On the other hand, the region also exhibits an average technical efficiency close to 90% (Table 9.6), with the notable exception of Model Y5, whose average technical efficiency is closer to 80%.

Confronted with the need to choose among different models, Model Y5 (defined by capital, labour, feed and fertiliser) would be the preferred options for Waikato-Taranaki. All parameters of the stochastic frontier under variable returns to scale are significant (Table 7.5) and maximum likelihood estimates for parameters of the stochastic frontier under constant returns to scale and variables mean-differenced are significant (Table A2.5 Appendix 2). Model K9 (defined by herd size, labour, capital and fertilizer) is another good option. All parameters of the stochastic frontier under variable and constant returns to scale are significant (Table 8.5 and Table A2.7). For Model Y5, capital is measured as the depreciation and interest on buildings, vehicles and machinery plus expenditure on repairs and maintenance, whereas for Model K9, capital is measured as expenditure on repairs and maintenance on buildings and machinery, fuel, electricity, rates and insurance, administration and miscellaneous. Interesting to note, though, are the values of the Pearson correlation coefficient (0.478) and the Spearman rank order correlation (0.594) (Table 9.3), that are significant but weak.

Finally, the fact that the region experienced very moderate to nil rates of technical progress, coupled with high values of structural efficiency (even though in some cases with high dispersion) suggest that new technologies are needed to shift the production frontier. However, the new technologies may not be available yet. Therefore, the industry requires investment in R&D or a shift in resources from current research into new areas. From a policy perspective, it is clear then that the recommendation should be to encourage investments in new R&D targeted to reduce the effects of technological constraints that impede the realisation of further productivity gains in the region.

9.3 Canterbury-Southland

Before undertaking the decomposition of TFP, a descriptive summary of the four models estimated for Canterbury-Southland is introduced.

Table 9.7 - Canterbury-Southland: summary of the four models

	Functional form	Technical progress	Technical efficiency (Structural efficiency)
Model J7	Translog	Neutral	Time varying (0.88)
Model L8	Translog	Non-neutral	Time-invariant (0.89)
Model Y5	Translog	Non-neutral	Time varying (0.86)
Model K9	Translog	Non-neutral	Time varying (0.90)

9.3.1 Technical efficiency change, as estimated by the four models

Technical efficiency increased by 15.7% for Model J7, 31.7% for Model Y5 and 8% for Model K9 over the whole period (Table 9.8), equivalent to a geometric mean of about 1.6%, 3.1% and 0.9% per annum for Models J7, Y5 and K9 respectively. Furthermore, for all models the annual rate of technical efficiency change was higher at the beginning of the period and declined gradually towards the end of the period. Conversely, Model L8 showed no changes in technical efficiency over the period (technical efficiency was time-invariant, η=0) (Section 6.3). Results for Models J7, Y5 and K9 indicate that Canterbury-Southland farms were catching up with the frontier over the whole period. It can also be seen that this process of catch-up is more active for Models J7 and Y5, as the average annual change in technical efficiency is at 1.6% and 3.1% per annum respectively. Given Models J7 and Y5, the region experienced technical regress (Table 9.9). Hence, as the frontier was shifting backwards, farms were able to catch up easier with the frontier. Conversely, for Model K9, this process is modest and relatively constant over the period. Estimates of average technical efficiency change differ significantly between models, resulting in cumulative changes ranging from nil (Model L8) to 31% (Model Y5).

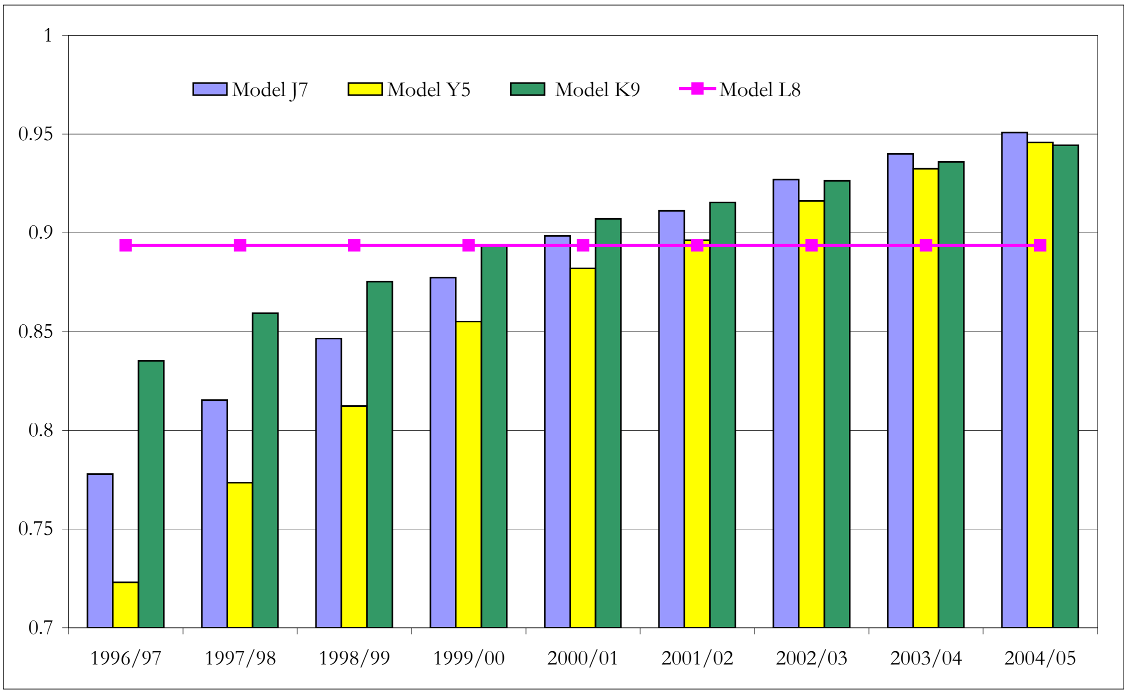
Table 9.8 - Cumulative indices of technical efficiency change for Canterbury-Southland region, estimated by the four models

	Model J7	Model L8	Model Y5	Model K9
1996/97	1,000	1,000	1,000	1,000
1997/98	1,034	1,000	1,067	1,013
1998/99	1,063	1,000	1,125	1,025
1999/00	1,086	1,000	1,171	1,036
2000/01	1,105	1,000	1,211	1,046
2001/02	1,121	1,000	1,243	1,055
2002/03	1,135	1,000	1,273	1,064
2003/04	1,147	1,000	1,297	1,072
2004/05	1,157	1,000	1,317	1,080
Cumulative (%)	**15.7%**	**0%**	**31.7%**	**8.0%**

Note: 1.000= no change

Average technical efficiency, for each season, differed significantly among models at the beginning of the period. However, these differences were much smaller by the end of the period (Figure 9.3). As expected, those models that experienced the lowest rates of technical progress (Model Y5 and Model J7) exhibited, in turn, the strongest improvement in structural efficiency over time. For example, in Model Y5, the structural efficiency climbed from 0.72 at the beginning of the period to 0.94 at the end of the period, whereas for Model K9, structural efficiency rose from 0.83 to 0.94 (Figure 9.3).

Figure 9.3 - Canterbury-Southland: changes in the structural efficiency for the four models, over the 10 years



The average estimates of farm efficiency for all the models proposed are reported below (Table 9.9). The average estimates shown for each farm were calculated as the geometric mean of the farm's annual efficiency measures obtain as per eq. 9 (Chapter 4). (Technical efficiency estimates for each farm at each time period and for each model are reported in Appendix 3.) The adjacent column (in grey) shows the farm's rank using each efficiency estimate. It can be seen that there is a difference in the magnitude of the efficiency estimates. The Pearson correlation coefficient shows a significant correlation in efficiency scores among alternative models. For example, efficiency estimates from models L8, J7 and Y5 with those obtained through model K9 have a Pearson correlation coefficient close to 1 and all are significant at 1%. All the other Pearson correlation coefficients are also significant. The Spearman rank correlation coefficients were all significant, and ranged between 0.671 (for Models L8/Y5) to 0.962 (for Models J7/Y5) (Table 8.12). Similar to the results reported for Waikato-Taranaki, these results suggest that both the precise value of technical efficiency and the farm ranking are not very dependent on the choice of the input/output set. Even though correlations are stronger than for the case of Waikato-Taranaki, more research in needed with a larger database.

Table 9.9 - Farm efficiency estimates and correlation of farm efficiency estimates given the alternative input/output sets for Canterbury-Southland

	Models							
	L8		J7		Y5		K9	
Farm	Av efficiency	**Rank**	Av efficiency	**Rank**	Av efficiency	**Rank**	Av efficiency	**Rank**
CS1	0,866	**11**	0,880	**11**	0,876	**8**	0,869	**12**
CS2	0,981	**1**	0,976	**2**	0,952	**2**	0,974	**3**
CS3	0,894	**9**	0,901	**8**	0,870	**10**	0,896	**7**
CS4	0,896	**8**	0,735	**15**	0,714	**14**	0,845	**14**
CS5	0,798	**15**	0,901	**7**	0,903	**5**	0,860	**13**
CS6	0,855	**12**	0,893	**9**	0,873	**9**	0,873	**11**
CS7	0,735	**16**	0,672	**16**	0,631	**16**	0,712	**16**
CS8	0,880	**10**	0,867	**13**	0,840	**13**	0,882	**10**
CS9	0,901	**7**	0,945	**4**	0,899	**6**	0,950	**6**
CS10	0,902	**6**	0,864	**12**	0,824	**12**	0,888	**9**
CS11	0,964	**5**	0,906	**6**	0,893	**7**	0,967	**4**
CS12	0,853	**13**	0,774	**14**	0,682	**15**	0,831	**15**
CS13	0,977	**2**	0,947	**3**	0,943	**3**	0,979	**2**
CS14	0,975	**3**	0,984	**1**	0,987	**1**	0,965	**5**
CS15	0,970	**4**	0,925	**5**	0,905	**4**	0,981	**1**
CS16	0,851	**14**	0,901	**10**	0,865	**11**	0,891	**8**
Pearson's correlation coefficients								
L8	1		0,697		0,677		0,920*	
J7			1		0,978 *		0,890*	
Y5					1		0,862*	
K9							1	
Spearman's rank order correlation								
L8		**1**		**0,703**		**0,671**		**0,850***
J7				**1**		**0,962***		**0,847***
Y5						**1**		**0,779***
K9								**1**

* significant at 1% level

9.3.2 Technical progress, as estimated by four models

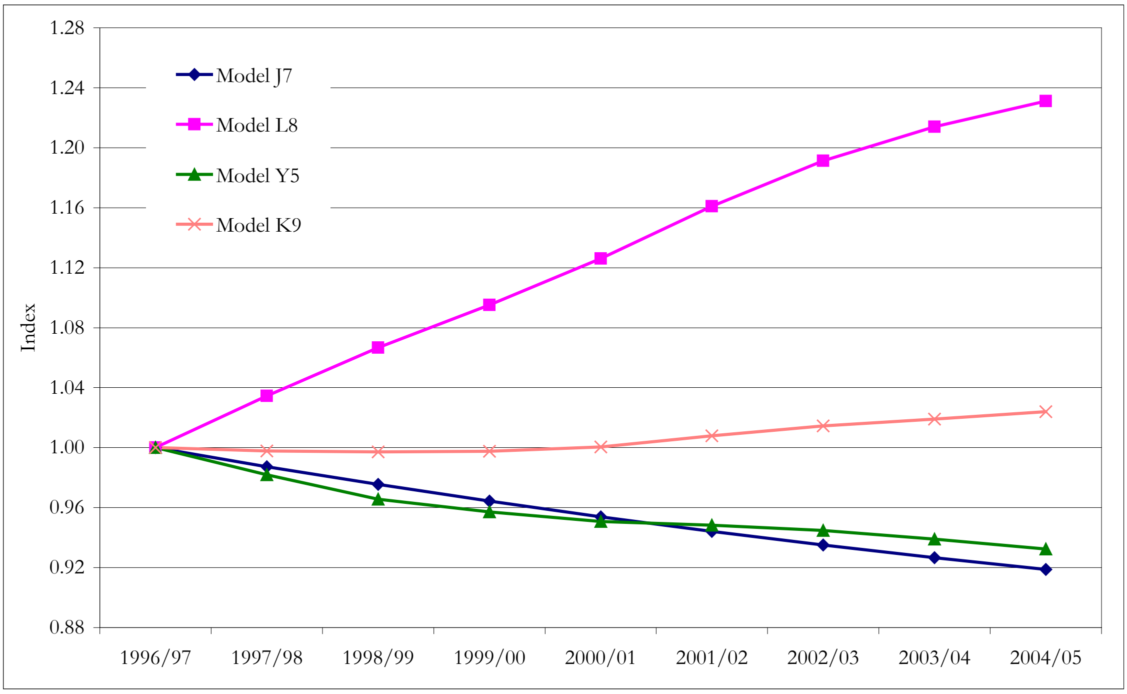
Technical progress declined in Models J7 and Y5 and increased in Models L8 and K9 over the period (Table 9.10). Overall, the decreases in technical progress were -8.1% in Model J7 and -6.8% in Model Y5 over the nine-year period, equivalent to a geometric average of -0.94% and -0.78% per annum respectively. Conversely, technical progress in Models L8 and K9 increased by 23.1% and 2.4% respectively over the nine-year period (Table 9.10 and Figure 9.4), equivalent to geometric averages of 2.3% and 0.3% per annum respectively.

Table 9.10 - Cumulative indices of change in technical progress for Canterbury-Southland region, estimated by the four models

	Model J7	Model L8	Model Y5	Model K9
1996/97	1,000	1,000	1,000	1,000
1997/98	0.987	1,035	0.982	0.998
1998/99	0.975	1,067	0.966	0.997
1999/00	0.964	1,095	0.957	0.998
2000/01	0.954	1,126	0.951	1,001
2001/02	0.944	1,161	0.948	1,008
2002/03	0.935	1,191	0.945	1,014
2003/04	0.927	1,214	0.939	1,019
2004/05	0.919	1,231	0.932	1,024
Cumulative (%)	**-8.1%**	**23.1%**	**-6.8%**	**2.4%**

With the exception of Model L8, all models showed a negative rate of technical progress during the first three seasons (Table 9.10 and Figure 9.4). The drop is more pronounced in Models J7 and Y5 than in Model K9. This technical regress may be due to the drought experienced by Canterbury during the initial seasons of the period of study (MAF, 2000). After these years, technical progress resumed for Model K9 but not for the other two. In contrast, technical progress in Model L8 increased almost at a constant rate up to season 2001/02 and kept on growing, albeit at decreasing rates over the second half of the period (Figure 9.4).

Figure 9.4 - Cumulative indices of technical progress for Canterbury-Southland region, estimated by the four models



The average estimates of farm's technical progress for all the models proposed are reported below (Table 9.11). The average estimates shown for each farm were calculated as the geometric mean of the farm's annual technical progress calculated as per eq. 19 (Chapter 4). (Technical progress estimates for each farm at each time period and for each model are reported in Appendix 3.) For example for Farm CS5, average technical progress over the period was 4.57%, 0.36%, 0.71%, 1.93% per annum given models L8, J7, Y5 and K9 respectively. The adjacent column (in grey) shows the farm's rank using each technical progress estimate. Farm CS5 is ranked 2nd for Model L8 and 1st for all other models. It can be seen that there is a difference in the magnitude of the TP estimates. The Pearson correlation coefficient shows a significant correlation in technical progress scores between alternative models, but the correlation is weak. For example, the Pearson correlation coefficient of technical progress as per model L8 with those obtained as per model J7 is 0.3437 and for models J7 and Y5 is 0.9412 (significant at 1%). The Spearman rank correlation coefficients were all significant but weak, ranging from 0.5059 (for Models L8/J7) to 0.9412 (for Models J7/Y5) (Table 9.11). It is worth noting that for farm's technical progress as per model L8, both the Pearson correlation coefficient and the Spearman rank correlation coefficient are lowest with respect to all other model estimates.

This confirms the concern about the suitability of the model for TP estimation due to the low statistical significance of some of the parameters as a result of multicollinearity. Results suggest that both the precise value of technical progress and the farm ranking are dependent on the choice of the input/output set. Given the weakness of the correlations, more research is needed with a larger database.

Table 9.11 – Farm average technical progress estimates and correlation of farm technical progress estimates given the alternative input/output sets for Canterbury-Southland

	Models							
	L8		J7		Y5		K9	
Farm	Av Tech Progress	**Rank**	Av Tech Progress	**Rank**	Av Tech Progress	**Rank**	Av Tech Progress	**Rank**
CS1	1,0390	**3**	0,9910	**3**	1,0004	**4**	1,0122	**2**
CS2	1,0293	**7**	0,9757	**10**	0,9840	**12**	1,0084	**6**
CS3	1,0326	**4**	0,9777	**11**	0,9938	**8**	0,9977	**12**
CS4	1,0314	**5**	0,9945	**2**	1,0047	**2**	1,0142	**3**
CS5	1,0457	**2**	1,0036	**1**	1,0071	**1**	1,0193	**1**
CS6	1,0213	**11**	0,9654	**13**	0,9784	**14**	0,9919	**14**
CS7	1,0623	**1**	0,9881	**6**	1,0037	**3**	1,0096	**4**
CS8	1,0323	**6**	0,9957	**4**	1,0034	**6**	1,0103	**5**
CS9	1,0235	**10**	0,9509	**16**	0,9681	**16**	1,0053	**8**
CS10	0,9996	**16**	0,9721	**12**	0,9863	**11**	0,9812	**16**
CS11	1,0215	**12**	0,9770	**9**	0,9881	**10**	1,0020	**9**
CS12	1,0169	**13**	0,9540	**15**	0,9718	**15**	0,9937	**13**
CS13	1,0068	**15**	0,9880	**8**	0,9941	**9**	1,0103	**7**
CS14	1,0079	**14**	0,9874	**5**	0,9943	**7**	0,9998	**11**
CS15	1,0271	**9**	0,9893	**7**	1,0019	**5**	1,0015	**10**
CS16	1,0246	**8**	0,9522	**14**	0,9782	**13**	0,9803	**15**
Pearson's correlation coefficients								
L8	1		0,3437		0,4661		0,5726	
J7			1		0,9544 *		0,6949	
Y5					1		0,5951	
K9							1	
Spearman's rank order correlation								
L8		**1**		**0,5059**		**0,6176**		**0,6676**
J7				**1**		**0,9412***		**0,7706**
Y5						**1**		**0,7029**
K9								**1**

* significant at 1% level

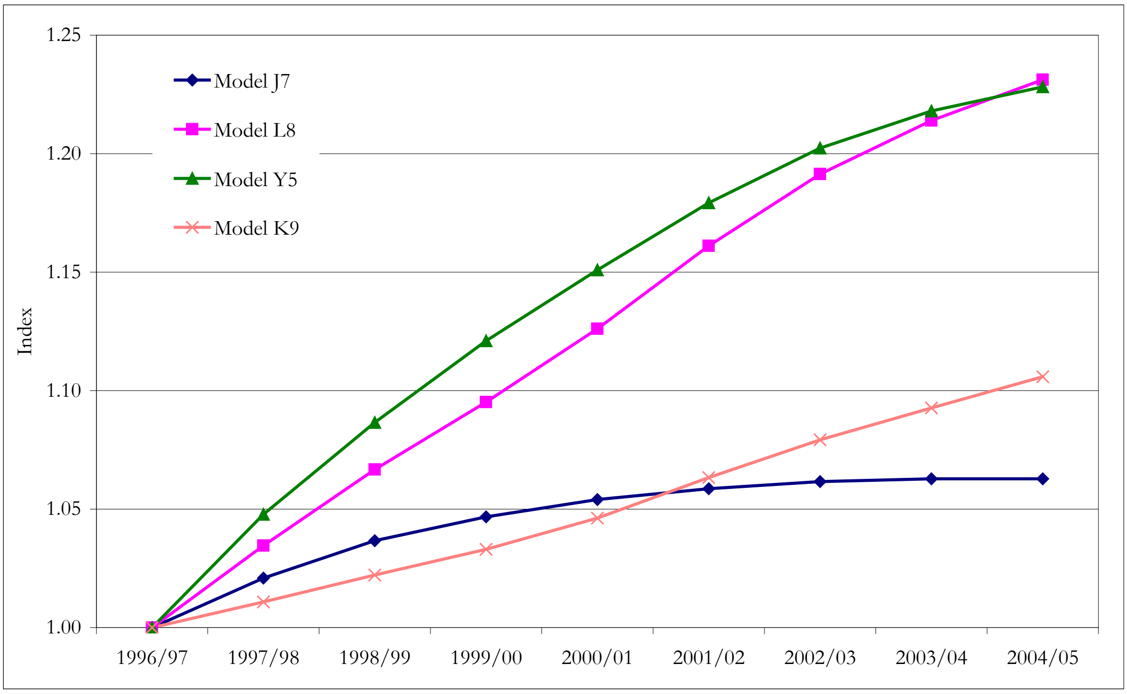
9.3.3 Total Factor Productivity change

When the amount of technical progress is combined with the technical efficiency change, a net increase in TFP is obtained for all models (Table 9.12 and Figure 9.5). TFP increased over the period by 6.3% for Model J7, 23.1% for Model L8, 22.8% for Model Y5 and 10.6% for Model K9 (Figure 9.5), equivalent to geometric means of 0.7%, 2.3%, 2.3% and 1.1% per annum for Models J7, L8, Y5 and K9 respectively (Table 9.13). All of these are well below the target measure of 4% annual increase, but Models L8 and Y5 give values closer to this target (TFP estimates for each farm at each time period and for each model are reported in Appendix 3).

Table 9.12 - Cumulative indices of total factor productivity, Canterbury-Southland region, estimated by the four models

	Model J7	Model L8	Model Y5	Model K9
1996/97	1,000	1,000	1,000	1,000
1997/98	1,007	1,003	1,004	1,006
1998/99	1,013	1,006	1,008	1,011
1999/00	1,020	1,010	1,012	1,017
2000/01	1,027	1,013	1,016	1,022
2001/02	1,034	1,016	1,020	1,028
2002/03	1,041	1,019	1,024	1,034
2003/04	1,048	1,023	1,028	1,040
2004/05	1,055	1,026	1,032	1,045
Cumulative (%)	**5.5%**	**2.6%**	**3.2%**	**4.5%**

Figure 9.5 - Cumulative indices of TFP change for Canterbury-Southland region, estimated by the four models



Even though the magnitudes of TFP change over the period differ slightly between Models J7 and K9 and between Models L8 and Y5, the sources of the change are different. For Model K9, both technical progress and technical efficiency change contributed to TFP change. Conversely, technical efficiency change is the most important source of TFP change in Model J7, as improvements in technical efficiency were able to offset the decline in technical progress (Table 9.13). In Model Y5, technical efficiency change was the main source of productivity gains, as improvements in efficiency overcame the decline in technical progress. In contrast, in Model L8, technical progress is the single source of productivity gain.

Table 9.13 - Average annual change in TFP and its sources by model for Canterbury-Southland estimated by the four models

	TFP	TEC	TP
Model J7	0.68%	1.63%	-0.94%
Model L8	2.34%	0.00%	2.34%
Model Y5	2.31%	3.11%	-0.78%
Model K9	1.12%	0.86%	0.26%

Model L8 (defined by herd size, labour, capital and area of farm) and Model K9 (defined by herd size, labour, capital and fertilizer) probably represent best the traditional technology applied in NZ. Estimates of TFPG, technical progress and technical efficiency change by Model K9 suggested that the farms were adopting technology very slowly (technical progress is 0.26% per annum) and that technical efficiency change was modest (at an average of 0.86% per annum). Technical efficiency change and technical progress are mutually reinforcing in Model K9 and hence productivity gains accelerated slightly over the period (Table 9.13 and Figure 9.5). Conversely, technical progress is the only source of TFP gains for Model L8.

Both Model L8 and Model K9 have two inputs in common: herd size and labour. The other two inputs in Model L8 are capital (K1, measured as the depreciation and interest on buildings, vehicles and machinery plus expenditure on repairs and maintenance) and farm area, whereas inputs for Model K9 are capital (K9, expenditure on repairs and maintenance on buildings and machinery, fuel, electricity, rates and insurance, administration and miscellaneous) and fertilizer expenditure.

The correlation between area of farm and fertilizer expenditure is 0.75. However, the growth rate of fertilizer expenditure (in real terms, averaged over farms) over the period is almost twice the growth rate in average area of farm. Similarly, the correlation between both measures of capital is higher, 0.91, and the growth rate of capital over the period is higher in Model L8 than in Model K9.

The measure of capital in Model K9 is an aggregation (in value terms) of different inputs. Prices for those inputs have evolved differently over time, e.g., fuel increased from 100 in 1996/97 to 147 in 2004/05, electricity from 100 to 137 and repairs and maintenance from 100 to 123 over the same period. Given that not all farms used these inputs (aggregated in "capital") in the same proportion, the measurement of capital can be responsible for the low values of technical progress. In addition, it was suggested that Model K9 suffers from multicollinearity and it may be a problem for the assessment of technical progress (Section 8.3).

Capital input (as measured in Model K9) was substituted by the measure of capital employed in model L8. Results of this model (defined by herd size, labour, K1 and fertiliser expenditure, results not included) suggested that a simplified translog production function was the best representation of the underlying technology. Even though results from this model also had problems of multicollinearity (albeit minor), technical progress (average for all sampled farms) was 2.1% per annum and technical efficiency was time-invariant. These values are closer to those estimated by Model L8.

Similarly, capital input, K1 (as measured in Model L8), was substituted by the measure of capital K9, in Model L8. The new model was defined by herd size, labour, farm area and K9 (results not included). Results indicated that the translog production function was the best representation of the underlying technology and that technical efficiencies had a half-normal distribution and were time invariant. Furthermore, the model had problems of multicollinearity (only 7 out of 21 coefficients were significant). Technical progress (average for all sampled farms) was 0.95% per annum. Both results suggest that the measurement of capital, K9, was responsible for the differences between models.

Model Y5 (defined by capital, labour, feed and fertiliser) can be an adequate representation of the new technology, where feed (forage or supplements) is brought from outside the farm system. Model J7 (defined by area of farm, labour, capital and intermediate input[21]) is intermediate between the other two models (L8 andK9). Models J7 and Y5 are alike in that the main source of TFPG is technical efficiency change. Insofar as the frontier shifted backwards (negative technical progress for Models J7 and Y5), farms are able to catch up easier with the frontier; gains arising from changes in technical efficiency are easier to

[21] Mostly comprised of feed and fertilizer expenditure

achieve. Therefore, TFP grows at a decreasing rate (Table 9.13 and Figure 9.5). Technical regress can be due to unmeasured input, e.g., deterioration in the quality of natural resources such as land (OECD, 2001). Alternatively, a newly-adopted technology may reduce productivity as a consequence of non-neutral technical change (Coelli et al., 1998 and Tauer, 1998), and any significant and sustained change in relative input prices are a possible source of measured productivity decline (Coelli et al., 2003 and OECD, 2001). Both models include feed and fertiliser as inputs in the production function, and the price index for both increased substantially over the period (Statistics NZ). Also, technical regress for Model Y5 was non-neutral. Why, then, is TP negative for CS and positive for WT? The quantities of feed and fertiliser used by farms in both regions are different. On average, WT dairy farms used 3.6 times less feed, fertiliser and intermediate input than CS dairy farms (Table 4.2 and Table 4.3). Furthermore, the ratio output to input is slightly higher for Waikato-Taranaki than for Canterbury-Southland.

For Canterbury-Southland, Model Y5 (defined by capital, labour, feed and fertiliser) is preferred to other models, as relatively more parameters of the stochastic frontier under variable returns to scale (Table 7.6) and under constant returns to scale and variables mean-differenced (Table A2.6 Appendix 2) are significant.

From a policy perspective, the recommendation would be the same for Models J7 and Y5. It is necessary to encourage investments in new R&D targeted to remove the technological constraints that impede the realization of further productivity gains in the region. The same recommendation applies to Model K9. For Model L8, a dynamic rate of technological progress coexists with no change in technical efficiency. Furthermore, the dispersion of farm technical efficiency is considerable relative to other models. Therefore, a policy directed to enhance the efficient use of technology is required to close the gap with the best-practice frontier.

9.4 Conclusion

A stochastic frontier production model was applied to estimate the MPI. MPI allows for the decomposition of TFPG into technical progress (TP) and technical efficiency change (TEC), providing individual (farm) estimates of technical efficiency, technical efficiency change and technical progress (Reported in Appendix 3).

Over the period of study, the relative contribution of TP and TEC to TFPG was different between regions. Results for Waikato-Taranaki are consistent in that small gains in TP are solely responsible for the small improvements in TFP of 0.29% to 0.59% per annum because TEC was zero for all models (Table 9.14). Improvements in TFP for Canterbury-Southland range from 0.68% (Model J7) to 2.34% (Model L8). Results showed that in three of the models, TEC was the main source of TFP improvements over the period of study. TEC was nil for one model and positive for the other three, differing significantly between 0.86% per annum (Model K9) and 3.1% per annum (Model Y5). TP ranged from -1% per annum (Model J7) to 2.3% per annum (Model L8). Two of the models (Model J7 and Model Y5) revealed technical regress, whereas the other two showed technical progress (Table 9.14).

Table 9.14 - Average annual change in TFP and its sources by model for both regions

	Waikato-Taranaki			Canterbury-Southland		
	TFP	TEC	TP	TFP	TEC	TP
Model J7	0.59%	0%	0.59%	0.68%	1.63%	-0.94%
Model L8	0.29%	0%	0.29%	2.34%	0.00%	2.34%
Model Y5	0.35%	0%	0.35%	2.31%	3.11%	-0.78%
Model K9	0.49%	0%	0.49%	1.12%	0.86%	0.26%

It is interesting to compare the results obtained here with those reported by other authors (Table 9.15). Even though not strictly comparable, Philpott (1994) estimated annual TFPG for the NZ dairy industry at 0.8% for the period 1973 to 1993. Pringle (2002) mentioned that on-farm productivity gains over the decade 1990 to 2000 were in the range of 1% to 1.3%. Similarly, Anderson and Johnson (2002) and Johnson and Forbes (2000) estimated on-farm productivity growth averaging 1.4% per annum for owner-operated dairy farms and 2.1% per annum for sharemilkers during the nineties. On-farm productivity growth as reported by this thesis ranged from 0.29% to 0.59% per annum for Waikato-Taranaki and from 0.68% to 2.3% per annum for Canterbury-Southland for the period 1996/97 to 2004/05.

Table 9.15 - Average annual change in TFP and its sources by model for both regions

Author	**Period**	**Methodology**	**Annual TFPG**
Philpott (1994)	1973–1993	Index number	0.8%
Pringle (2002)	1990–2000	Index number	1% to 1.3%
Anderson and Johnson (2002) & Johnson and Forbes (2000)	1990s	Index number	1.4% owners 2.1% sharemilkers
Laca-Vina (2007)	1997–2005	SFA-Malmquist	0.29%–0.59% WT 0.68%–2.3% CS

Average efficiency for Waikato-Taranaki was almost the same for Model L8 (91%), Model K9 (89%) and Model J7 (87%). Average efficiency was lowest for Model Y5 (81%) (Figure 9.3). Similarly, average efficiency for Canterbury-Southland was almost the same for Model L8 (89%), Model K9 (90%) and Model J7 (88%), and was lowest for Model Y5 (86%) (Table 9.7). Jaforullah and Devlin (1996), with farm-level data for 1991/92, estimated an average efficiency (using SFA) of 90% ranging from 76% to 96%. Present estimates of average efficiency for Waikato-Taranaki are comparable: 91% (for Model L8), 89% (Model K9) and 87% (Model J7); and so are the ranges 76% to 98% (Figure 9.4). Given the results of Model Y5, farm efficiency range is similar but average efficiency is significantly lower (81%). With respect to Canterbury-Southland average efficiency for the last season, the Jaforullah and Devlin (1996) estimate is comparable. Technical efficiency for individual farms ranged from a low of 76% to a high of 98% in both studies.

The robustness of technical efficiency estimates (and hence, technical efficiency change) and technical progress estimates to the input/output set chosen was addressed by comparing farm-level estimates obtained by the different models using the Pearson correlation coefficient and the Spearman rank order correlation. Even though results are not conclusive, evidence suggests that efficiency estimates are not very sensitive to the choice of input/output set. Based on analysis of the two regions, it was found that the magnitude of technical efficiency estimates from the four models is different, but estimates are strongly correlated. Interestingly, evidence of the robustness of technical efficiency estimates to input/output set is stronger for estimates from Canterbury-Southland than for estimates from Waikato-Taranaki. Pearson correlation coefficient and Spearman rank order correlation, even though significant, are higher for Canterbury-Southland (Table 9.9) than for Waikato-Taranaki (Table 9.3). For example, for Waikato-Taranaki, Pearson correlation coefficient ranges from 0.487 to 0.885 and the Spearman rank order correlation ranges from 0.503 to 0.903 (Table 9.3). For Canterbury-Southland, Pearson correlation coefficient ranges from 0.677 to 0.978 and the Spearman rank order correlation ranges from 0.671 to 0.962 (Table 9.9). Therefore, if the interest of the researcher is measuring technical efficiency, estimates are similar regardless of the input/output set.

Results about the sensitivity of technical progress estimates to alternative input/output sets are mixed. It is worth mentioning that no such analysis could be performed for Waikato-Taranaki as the preferred functional form was of a Cobb-Douglas type and hence by definition all farms have the same rate of TP over all years. For Canterbury-Southland, Pearson correlation coefficient ranges from 0.3437 to 0.9544 and the Spearman rank order correlation ranges from 0.5059 to 0.9412 (Table 9.11). It seems that rankings tend to be more stable (less sensitive) to the choice of input/output set than magnitude. Evidence suggests that technical progress estimates will be influenced by input/output sets. Further analysis with a larger database is needed, as the sensitivity of technical efficiency estimates (and hence, technical efficiency change) and technical progress estimates to the input/output set remains an issue of contention.

CHAPTER 10

10 Conclusion

10.1 Introduction

This chapter begins with a brief comment about the selection of the topic followed by an evaluation of the approach. The next section reviews the main findings of the research and their policy implications. The last section is dedicated to the "would-like-to-do list" and discussion of areas for further research.

10.2 Milking the productivity index

The NZ dairy industry is aiming for a 4% annual growth in on-farm TFP in order to secure its competitive advantage and enhance NZ dairy farmers' profitability. Previous studies indicated that the industry was not achieving the target. TFP is an adequate measure of performance to benchmark and monitor farms. It is the most encompassing measure of performance, as it ideally includes all inputs and outputs used in the production process. It is the "real" (or "physical" as opposed to monetary) component of profitability. TFP is an ex-ante determinant of profitability change, rather than a consequence of it and unlike prices, quantities of inputs and outputs are, to some extent, under the control of management. It was clear, though, that the industry was unable to link the 4% annual growth in productivity to the farm level. The industry was not providing the farmers with any individual (farm level) indicator with which to benchmark and monitor their progress. Succinctly, can TFP be used to guide policy decisions at an industry level and concurrently be an instrument for strategic management at the farm level?

The availability of panel data allowed the estimation of TFP using the MPI. The index is based on distance functions and is superior to alternative indexes of productivity growth (such as the Törnqvist index and the Fisher ideal index) because it is based only on quantity data and makes no assumptions regarding the firm's behaviour. Furthermore, it can be decomposed into technical efficiency change (whether farms are getting closer to the frontier) and technical change (whether the production frontier is shifting outwards over time). Both components are in turn driven by different factors, allowing then for a deeper view into productivity growth. At the same time, individual (farm) estimates of TFP, TC and TEC are obtained (Reported in Appendix 3). SFA was used to compute the distance functions required to estimate the Malmquist TFP index because it allows for traditional hypothesis testing, necessary to evaluate differences in technology between regions. Also, SFA has a composed error term with a stochastic component (to account for random errors not under the control of the firm) and a deterministic component (that captures departures from maximum output, i.e., inefficiency) that would help to attenuate some of the shortcomings of the data (data were collected for purposes other than the estimation of productivity and the number of observations are small). MAF Policy supplied panel data. Even though the number of observations was not the desired one (albeit sufficient) the relevance of the topic to the NZ dairy industry encouraged the author to continue.

10.3 Main findings and policy implications

Differences in technology between both regions (traditional vis-à-vis non-traditional) defined in this study were uncovered. First, a dummy variable was introduced in the pooled model, following the method of Bravo-Ureta and Rieger (1991), Hallam and Machado (1996) and Kumbhakar and Heshmati (1995). The regional dummy was included in the pooled model (all farms from both regions) to test whether regional differences exist (Section 4.7, Chapter 4).

Farms located in Waikato-Taranaki were used as reference group. For all alternative input/output sets defined, the coefficient on the regional dummy was positive and significantly different from zero. Therefore, based on this result, there was *a priori* evidence that the stochastic frontier model differed between regions, indicating that both regions may not be operating under the same technology (Table 10.1). Furthermore, based on the sign of the dummy, it could be advanced that, for all the production functions defined by the input/output sets, Canterbury-Southland sampled farms were, on average, more productive than sampled farms in Waikato-Taranaki, *ceteris paribus*.

The value of the coefficient on the regional dummy ranged from 0.1082 for Model K9 to 0.1831 for Model Y5, implying that sampled farms in Canterbury-Southland (non-traditional dairy regions) were, on average, between 11% to 18% more productive than sampled farms in Waikato-Taranaki (traditional dairy regions), *ceteris paribus*. The value of the coefficient was fairly consistent across all alternative input/output sets, denoting the robustness of the result.

Table 10.1 - Summary of technological differences between regions for all models

Model	Coefficient Regional dummy	*t-value*	LR test H_0: both regions share same technology
J7	0.1097	2.4537 **	Reject H_0 (Section 5.1.4)
L8	0.1540	4.5624 **	Reject H_0 (Section 6.1.4)
Y5	0.1831	4.8991 **	Reject H_0 (Section 7.1.4)
K9	0.1082	3.366 **	Reject H_0 (Section 8.1.4)

Note: *** - significant at 1% level (p<0.01)
** - significant at 5% level (p<0.05)
* - significant at 10% level (p<0.10)

As was previously mentioned, the value of the coefficient of the regional dummy included in the pooled sample indicated that both regions (traditional vis-à-vis non-traditional) might not be operating under the same technology. Following Battese, Rao and O'Donnell (2004) and Kumbhakar, Biswas and Bailey (1989) the appropriateness of dividing the sample into two regions was tested by a likelihood-ratio test for all the alternative input/output sets. The null hypothesis that both regions share the same underlying technology was rejected for all the alternative input/output sets, confirming the *a priori* result obtained by using the regional dummy in the pooled stochastic frontier. Therefore, according to the log-likelihood ratio test, farm-level data in the two regions were not generated from a single production frontier and the same underlying technology (Table 10.1).

It is worth mentioning that average size of Canterbury-Southland sampled farms is larger than average farm size of Waikato-Taranaki farms. Furthermore, average farm size of Canterbury-Southland sampled farms is larger than the regional average (LIC data). Conversely, average farm size of Waikato-Taranaki sampled farms is smaller than the regional average. Therefore, more studies with a larger database are required to ascertain whether technological differences are due to location or to scale.

None of the NZ dairy regions included in this analysis is achieving the 4% productivity target set by the dairy industry. For Waikato-Taranaki, technical progress is the sole source of TFPG for all models, i.e., technical efficiency change is zero meaning that all farms considered maintain the same distance with respect to the frontier for all the period under study. Furthermore, the rate of technical progress and hence TFP (given that TEC is zero) is positive and small in all cases ranging from 0.29% per annum to 0.59% per annum.

For Canterbury-Southland, estimates of TFP are positive for all models ranging from 0.68% per annum to 2.34% per annum. However, results are mixed regarding to the sources of productivity change, showing great variability in the magnitude of both TP and TEC. In two cases, results indicate a negative rate of TP offset by TEC. In other case TP was the sole contributor to TFP. Finally, TP and TEC jointly contribute to TFPG for the last model. TP ranges from -0.94% to 2.34% per annum and TEC ranges from 0% to 3.11% per annum.

The most important implication for the NZ dairy industry and for those institutions responsible for helping the farmers to achieve the productivity target refers to the need of tailoring the approach and limiting the geographical scope of R&D projects. Findings described here support the results from farmers' interviews reported by Massey et al. (2002), which suggested the need for an increase in applied location-specific research vis-à-vis pure and strategic research carry-out in research stations.

Given the high levels of farm technical efficiency in both regions, the NZ dairy industry cannot expect to achieve major productivity gains through technical efficiency change. Instead, a major concern is the meagre gain in technical progress experienced by both regions. The recommendation should be to encourage investments in new R&D. In doing so, the industry will remove technological constraints that impede the realisation of further productivity gains. Once-a-day-milking, new, more productive pastures with better quality and improvements in the digestibility of pasture are some of the elements that will certainly help to shift the technological frontier. OAD may certainly reduce productivity per cow; however, it increases labour productivity (same workers can milk another herd) and capital productivity (the milking shed can be used for another herd, i.e., cost sharing, fewer inputs). The overall outcome on TFP is unknown. Interestingly, the methodology proposed to assess differences in technology between regions can be used to assess TFP differences among farms and also among cows as a result of OAD.

The robustness of farm technical efficiency estimates (and hence technical efficiency change) and technical progress estimates to the input/output set chosen was addressed by comparing farm-level estimates obtained by the different models using the Pearson correlation coefficient and the Spearman rank order correlation. Even though results are not conclusive, evidence suggests that efficiency estimates are not very sensitive to the choice of input/output set. Conversely, results suggest that technical progress estimates will be influenced by input/output set. It seems that rankings tend to be more stable (less sensitive) to the choice of input/output set than magnitude. Further analysis with a larger database is needed, as the sensitivity of technical efficiency estimates (and hence technical efficiency change) and technical progress estimates to the output/output set remains an issue of contention.

As mentioned before, none of the regions were able to achieve the growth target. However, some of the farms in Canterbury-Southland were able to achieve and even surpass the TFPG target. It can be seen that "average" measures either at regional or national level offer limited information. The MPI makes available a vast amount of information at the farm level that can be aggregated later, if desired. Therefore, if the objective of the NZ dairy industry is to improve farmers' profitability and the target measure is productivity growth, the measurement instrument should be the MPI.

10.4 Limitations and future research

Although this study is the first attempt to investigate the productivity, technical progress and efficiency change for dairy farming in a regional context, there are several limitations that have to be taken into account when we try to interpret its results. These limitations, mainly due to data unavailability, can be addressed by future research.

First, it is noted that the SFA model used in this study to estimate the MPI is capable of handling one output. It is well-known that dairy farms not only produce milk, but also beef and forage and in some cases, sell machinery services to fellow farmers. As such, future research can look into these effects and examine whether the same results are obtained when more than one output is considered. Estimation of MPI through DEA would allow considering more than one output. This would also allow testing allocative inefficiency with regards to outputs.

Second, due to data availability, the study was limited to 16 farms in Waikato-Taranaki and Canterbury-Southland. Other regions like Wellington, Wairarapa, Otago and Northland were not included in our study. These regions have been important players in the recent development of the NZ dairy industry. For instance, farm conversions in Wellington and Wairarapa increased over recent years. Northland has unique weather characteristics that can influence the transferability of research (Alston, 2001). Moreover, the higher variability observed for Canterbury-Southland estimates might be related to differences in production technology between Canterbury and Southland. Given the number of observation in the database, it was impossible to evaluate such a hypothesis. A similar hypothesis can be tested for Waikato-Taranaki, should enough data are available.

As mentioned before, average size for farms in Canterbury-Southland is larger than for farms in Waikato-Taranaki (Chapter 2). Hence, the regional dummy may be capturing part of the size effect on productive differences. The small size of the database does not allow any effect of size to be separated from the location effect and hence to evaluate whether size differences between farms is partly responsible for differences in technologies. Therefore, further studies are required to assess whether scale of operation is responsible for differences in technology.

As was said before, the database obtained to perform the study was collected for other purposes. Hence, some information that would have been helpful to better explain the results was not collected. The input "cows," for example, has to be corrected for the improvements in the genetic merit of the cows, particularly when the period of the study is large. In the present case, if a 20% replacement rate were assumed, in nine years the herd would have changed almost twice. The technical change embodied in the new cows would not be capture unless a "corrected" number of cows is used. Similarly, the number of cows used has to be adjusted by weight, or instead of number of cows, the input "kgs of cows" has to be used. The fertiliser input has to be corrected, as part of it is used as feed input. In turn, the feed input should be normalised (homogenised) in terms of metabolised energy.

That way it would be possible to evaluate the substitution elasticity between alternative inputs in the diet: feed (concentrate, silage, other) and grass as a way to identify ongoing trends and the response of production to its use.

It may be argued that sharemilkers have a higher incentive than owner-operators to achieve a higher productivity. In this way they could obtain more income, speeding up the process of becoming an owner. It might be useful to test whether sharemilkers achieve a higher productivity than owner-operators and ascertain the relative impact of sharemilking agreements on TFPG. If the impact is sizeable and sharemilkers are those pushing the technological frontier, the industry has to evaluate the impact of a slowdown in the sharemilking progression that high values of land can provoke.

An important area of future research is related to the understanding of the causes of inefficiency. This type of information has to be collected at the same time as most of the variables that may explain inefficiency as either dynamic (age, size, etc,) or having a long-term effect (education, investments, location, etc.). The MAF database does not give any information about farmers that can help to explain differences in efficiency. Similarly, it is also important to determine the drivers of TFP, TP and TEC change, i.e., the factors/determinants of their behaviour (Coelli, 1995 and Perelman, 1995). Both identifying the determinants of inefficiency and the drivers of TFP, TP and TEC are crucial for adequately target R&D and extension services. These would require gathering an extensive database. Given the costs of that kind of endeavour, it may pay off for stakeholders to act together.

Finally, the original idea was to discuss results with Dexcel, MAF and people at Massey at different seminars at the University. Given the state of affairs described above, the discussion of the results took place at La Estanzuela, an experimental station of the INIA (National Institute of Agricultural Research) of Uruguay on September 2007. The core of dairy research in Uruguay takes place at the La Estanzuela experimental station. All the researchers of the group were present and the seminar spanned almost four hours. The high calibre of the audience was undoubtedly challenging, however the discussion was centred on technical aspects of productivity and policy implications and not on NZ dairy industry and regional characteristics. It is recognised that conclusions would have been richer would a discussion with NZ experts have taken place.

10.5 Final comments

In the near future, changes in the geographical distribution of milk production will continue, perhaps intensifying the need for a regional approach to R&D. As mentioned earlier, if the pathway to increases in milk production differs across regions, then technological requirements will certainly be different. Alternatively, it might be the case for regions to be at a different stage in the development process, and therefore with unique technological needs. Whatever the case, it seems clear that it would demand increasing coordination and cooperation from R&D agencies and the extension services.

Two characteristics made TFP an adequate measure of performance with which to benchmark and monitor a group of farms (Balk, 2003). First, unlike prices, quantities of inputs and outputs are, to some extent, under the control of management. Second, TFP is an ex-ante determinant of profitability change rather than a consequence of it. The MPI looks promising as an instrument to generate farm-level information to help farmers achieve the growth target. However, estimation of TFP at the farm-level requires data demanding detailed information on inputs used and output produced per farm.

The recent launch of the dairy base can be used to set up a benchmarking and monitoring plan where those farms that achieve a higher efficiency and productivity could became case studies and trial farms to others interested in improving their productivity. Given the interest in identifying those farms that are performing best, DEA can be used to estimate the distance functions of the MPI. DEA is less stringent in terms of the calculations and it identifies peer farms with which to benchmark. The number of observation will be an issue, as at least 15% to 20% of the farms have to participate in the survey. However, it is difficult to draw up the boundaries of the amount and type of information to be asked, and based on what was done here, information has to come from four main areas: productive, financial, socio-cultural and geographical. Productive information refers to inputs and outputs used in the production process. An important refinement would be to gather information on individual prices paid for inputs. It would also be important to obtain good information about labour use (either in physical units or in monetary units) with special attention to owners' dedication. Financial information about investments, interests paid and expenditure on repairs and maintenance would help to estimate a measure of capital, avoiding the use of book value of assets (which most of the time depends on taxation).

Socio-cultural information would allow analysing the causes of inefficiency and when gathered year after year would help track down and ascertain the impact of such a programme. Finally, geographical information will complement socio-cultural variables in explaining inefficiency and in identifying local needs. For example, it was discussed that the number and proximity of dairy farms in Waikato-Taranaki permitted the development of a good network of services, reducing the use of own capital vis-à-vis Canterbury-Southland. The selection of TFP as a target measure to guide on-farm improvements and the use of MPI open a wide range of interesting research opportunities, some of which have been mentioned above.

Appendix 1

Results for Model J7

Table A1.1 - Data for Canterbury-Southland: Maximum likelihood estimates for parameters of the stochastic frontier for Model J7 under VRS (variable returns to scale), variables mean-differenced

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	0.2078	2.6398 **
Area (A)	β_1	0.0974	1.9987 *
Labour (L)	β_2	0.3896	7.5026 ***
Capital (K2)	β_3	0.0984	2.0441 **
Intermediate input (II)	β_4	0.2919	6.6302 ***
Year (Y)	β_t	-0.0274	-1.8212 *
$(\text{Year})^2$	β_{tt}	0.0016	1.7895 *
$(A)^2$	β_{11}	-0.2079	-0.9337
(A) x (L)	β_{12}	-0.2273	-0.5994
(A) x (K2)	β_{13}	0.1871	0.5939
(A) x (II)	β_{14}	0.5560	1.8478 *
$(L)^2$	β_{22}	0.0377	0.1263
(L) x (K2)	β_{23}	0.0861	0.2466
(L) x (II)	β_{24}	-0.6968	-2.2966 **
$(K2)^2$	β_{33}	-0.1088	-0.5596
(K2) x (II)	β_{34}	0.3955	1.2712
$(II)^2$	β_{44}	0.0438	0.2562
Variance parameters			
Sigma	σ^2	0.0127	3.5560 **
Gamma	γ	0.3270	1.7902 *
Technical inefficiency effect	μ_i	Restricted to zero	
Time varying inefficiency	η	0.2085	4.6356 **

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Results for Model L8

Table A1.2 - Data for Canterbury-Southland: Maximum likelihood estimates for parameters of the stochastic frontier for Model L8 under VRS (variable returns to scale), variables mean-differenced

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	0.0543	1.2323
Cow (C)	β_1	0.8602	6.1904 **
Labour (L)	β_2	0.0687	1.5597
Area (A)	β_3	0.2590	3.0218 **
Capital (K2)	β_4	-0.1371	-1.7822 *
Year (Y)	β_t	0.0218	1.7885 *
$(\text{Year})^2$	β_{tt}	-0.0018	-1.3041
(C) x (Y)	β_{1t}	0.0156	0.5571
(L) x (Y)	β_{2t}	-0.0078	-0.4195
(A) x (Y)	β_{3t}	-0.0622	-4.1176 **
(K2) x (Y)	β_{4t}	0.0470	3.1163 **
$(\text{C})^2$	β_{11}	-0.0159	-0.0278
(C) x (L)	β_{12}	0.3081	0.4055
(C) x (A)	β_{13}	-0.0604	-0.1131
(C) x (K2)	β_{14}	-0.1355	-0.3018
$(\text{L})^2$	β_{22}	-0.2505	-0.6986
(L) x (A)	β_{23}	-0.2201	-0.6735
(L) x (K2)	β_{24}	0.1149	0.3583
$(\text{A})^2$	β_{33}	-0.0900	-0.3436
(A) x (K2)	β_{34}	0.7282	2.7059 **
$(\text{K2})^2$	β_{44}	-0.2182	-1.5039
Variance parameters			
Sigma	σ^2	0.0252	2.7532 **
Gamma	γ	0.7890	9.5645 ***
Technical inefficiency effect	μ_i	Restricted to zero	
Time-varying inefficiency	η	Restricted to zero	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Results for Model Y5

Table A1.3 - Data for Canterbury-Southland: Maximum likelihood estimates for parameters of the stochastic frontier for Model Y5 under VRS (variable returns to scale), variables mean-differenced

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	0.2024	2.1977 **
Capital (K2)	β_1	-0.1019	-1.7935 *
Labour (L)	β_2	0.6376	5.0541 **
Feed (FE)	β_3	0.0632	1.8167 *
Fertilizer (FT)	β_4	0.2081	2.0540 **
Year (Y)	β_t	-0.0168	-1.7637 *
$(\text{Year})^2$	β_{tt}	0.0007	0.3406
(K2) x (Y)	β_{1t}	0.0518	2.4597 **
(L) x (Y)	β_{2t}	-0.0438	-2.1404 **
(FE) x (Y)	β_{3t}	0.0148	1.6000
(FT) x (Y)	β_{4t}	-0.0150	-0.8817
$(\text{K2})^2$	β_{11}	-0.2483	-1.2083
(K2) x (L)	β_{12}	0.3682	1.0268
(K2) x (FE)	β_{13}	0.2959	1.7877 *
(K2) x (FT)	β_{14}	0.1323	0.6134
$(\text{L})^2$	β_{22}	0.0823	0.3124
(L) x (FE)	β_{23}	-0.5651	-3.8523 **
(L) x (FT)	β_{24}	-0.3585	-1.3723
$(\text{FE})^2$	β_{33}	0.3220	4.9163 **
(FE) x (FT)	β_{34}	-0.3675	-3.0092 **
$(\text{FT})^2$	β_{44}	0.3029	2.5711 **
Dummy for policy change	*Dpc*	-0.0717	-1.8761 *
Variance parameters			
Sigma	σ^2	0.0122	3.8161 **
Gamma	γ	0.4028	2.4458 **
Technical inefficiency effect	μ_i	Restricted to zero	
Time-varying inefficiency	η	0.2293	6.3693 ***

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Results for Model K9

Table A1.4 - Data for Canterbury-Southland: Maximum likelihood estimates for parameters of the stochastic frontier for Model K9 under VRS (variable returns to scale), variables mean-differenced

Variables	Parameter	Coefficient	t-value
Stochastic Frontier			
Constant	β_0	0.1033	1.9385 *
Cows (CW)	β_1	0.9843	4.7702 **
Labour (L)	β_2	0.0297	1.5265
Fertilizer (FT)	β_3	-0.0782	-1.8809 *
Capital (K9)	β_4	-0.0687	-1.8508 *
Year (Y)	β_t	0.0157	1.9358 *
$(\text{Year})^2$	β_{tt}	-0.0025	-1.2809
(CW) x (Y)	β_{1t}	-0.0677	-1.9099 *
(L) x (Y)	β_{2t}	0.0155	0.5528
(FT) x (Y)	β_{3t}	0.0457	3.4547 **
(K9) x (Y)	β_{4t}	0.0322	2.5298 **
$(\text{CW})^2$	β_{11}	0.4270	0.5040
(CW) x (L)	β_{12}	0.2685	0.1817
(CW) x (FT)	β_{13}	-0.3917	-1.1811
(CW) x (K9)	β_{14}	0.5882	1.2836
$(\text{L})^2$	β_{22}	-0.7177	-1.0531
(L) x (FT)	β_{23}	0.1071	0.3082
(L) x (K9)	β_{24}	0.1991	0.4833
$(\text{FT})^2$	β_{33}	0.0759	0.6255
(FT) x (K9)	β_{34}	-0.1669	-0.8351
$(\text{K9})^2$	β_{44}	-0.2941	-2.5046 **
Variance parameters			
Sigma	σ^2	0.0107	2.7812 **
Gamma	γ	0.4902	2.7872 **
Technical inefficiency effect	μ_i	Restricted to zero	
Time varying inefficiency	η	0.1476	2.8781 **

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Appendix 2

Results for Model J7

Table A2.1 - Data for Waikato-Taranaki: Maximum likelihood estimates for parameters of the stochastic frontier for Model J7 under CRS (constant returns to scale)

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	5.8599	30.7125 ***
Area (A)	β_1	0.2762	
Labour (L)	β_2	0.2970	6.2569 ***
Capital (K2)	β_3	0.0273	0.5954
Intermediate input (II)	β_4	0.3995	8.1259 ***
Year (Y)	β_t	0.0067	2.0711 **
Variance parameters			
Sigma	σ^2	0.0427	2.6078 **
Gamma	γ	0.8284	11.3282 ***
Technical inefficiency effect	μ_i	Restricted to zero	
Time varying inefficiency	η	Restricted to zero	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Table A2.2 - Data for Canterbury-Southland: Maximum likelihood estimates for parameters of the stochastic frontier for Model J7 under CRS (constant returns to scale), variables mean-differenced

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	0.1447	1.9097 *
Area (A)	β_1	0.1694	
Labour (L)	β_2	0.3735	6.9291 ***
Capital (K2)	β_3	0.1118	2.2625 **
Intermediate input (II)	β_4	0.3453	8.1929 ***
Year (Y)	β_t	-0.0136	-1.6588
$(\text{Year})^2$	β_{tt}	0.0003	1.1590
$(A)^2$	β_{11}	-0.9056	
(A) x (L)	β_{12}	0.4904	
(A) x (K2)	β_{13}	-0.0864	
(A) x (II)	β_{14}	0.5016	
$(L)^2$	β_{22}	0.5096	1.7509
(L) x (K2)	β_{23}	-0.1440	-0.3842
(L) x (II)	β_{24}	-0.8560	-2.7529 *
$(K2)^2$	β_{33}	-0.0367	-0.1760
(K2) x (II)	β_{34}	0.2671	0.8025
$(II)^2$	β_{44}	0.0872	0.5241
Variance parameters			
Sigma	σ^2	0.0136	4.5401 **
Gamma	γ	0.1683	0.9875
Technical inefficiency effect	μ_i	Restricted to zero	
Time varying inefficiency	η	0.1960	2.5643 **

Note: *** - significant at 1% level ($p<0.01$)

** - significant at 5% level ($p<0.05$)

* - significant at 10% level ($p<0.10$)

Results for Model L8

Table A2.3 - Data for Waikato-Taranaki: Maximum likelihood estimates for parameters of the stochastic frontier for Model L8 under CRS (constant returns to scale)

Variables	Parameter	Coefficient	t-value
Stochastic Frontier			
Constant	β_0	5.7763	31.1246 ***
Cow (C)	β_1	1.0443	
Labour (L)	β_2	0.0957	1.8516 *
Area (A)	β_3	-0.1547	-2.0955 **
Capital (K2)	β_4	0.0946	1.9618 *
Year (Y)	β_t	0.0032	1.8435 *
Variance parameters			
Sigma	σ^2	0.0229	2.7841 **
Gamma	γ	0.6668	5.0527 **
Technical inefficiency effect	μ_i	Restricted to zero	
Time-varying inefficiency	η	Restricted to zero	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Table A2.4 - Data for Canterbury-Southland: Maximum likelihood estimates for parameters of the stochastic frontier for Model L8 under CRS (constant returns to scale), variables mean-differenced

Variables	Parameter	Coefficient	t-value
Stochastic Frontier			
Constant	β_0	0.0278	0.7377
Cow (C)	β_1	0.7652	
Labour (L)	β_2	0.1218	1.3622
Area (A)	β_3	0.2869	3.6248 **
Capital (K2)	β_4	-0.1740	-2.2893 **
Year (Y)	β_t	0.0317	2.3703 **
$(\text{Year})^2$	β_{tt}	-0.0026	-2.0374 **
(C) x (Y)	β_{1t}	0.0303	
(L) x (Y)	β_{2t}	-0.0240	-1.4838
(A) x (Y)	β_{3t}	-0.0622	-4.8955 ***
(K2) x (Y)	β_{4t}	0.0559	3.9894 **
$(C)^2$	β_{11}	0.4397	
(C) x (L)	β_{12}	0.1210	
(C) x (A)	β_{13}	-0.0342	
(C) x (K2)	β_{14}	-0.5266	
$(L)^2$	β_{22}	0.0516	0.1524
(L) x (A)	β_{23}	-0.2206	-0.7383
(L) x (K2)	β_{24}	0.0480	0.1590
$(A)^2$	β_{33}	-0.4371	-2.0373 **
(A) x (K2)	β_{34}	0.6918	2.9424 **
$(K2)^2$	β_{44}	-0.2132	-1.4113
Variance parameters			
Sigma	σ^2	0.0217	2.9469 **
Gamma	γ	0.7258	7.0961 ***
Technical inefficiency effect	μ_i	Restricted to zero	
Time-varying inefficiency	η	Restricted to zero	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Results for Model Y5

Table A2.5 - Data for Waikato-Taranaki: Maximum likelihood estimates for parameters of the stochastic frontier for Model Y5 under CRS (constant returns to scale), variables mean-differenced

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	5.9958	27.6496 ***
Capital (K2)	β_1	0.1505	
Labour (L)	β_2	0.4018	8.4004 ***
Feed (FE)	β_3	0.2063	6.9879 ***
Fertilizer (FT)	β_4	0.2414	5.8631 ***
Year (Y)	β_t	0.0039	1.7847 *
Variance parameters			
Sigma	σ^2	0.0199	3.4770 **
Gamma	γ	0.5221	4.4991 ***
Technical inefficiency effect	μ_i	0.2039	3.7076 **
Time-varying inefficiency	η	Restricted to zero	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Table A2.6 - Data for Canterbury-Southland: Maximum likelihood estimates for parameters of the stochastic frontier for Model Y5 under CRS (constant returns to scale), variables mean-differenced

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	0.2472	2.8440 **
Capital (K2)	β_1	-0.0902	
Labour (L)	β_2	0.7768	7.2613 ***
Feed (FE)	β_3	0.0934	1.8152 *
Fertilizer (FT)	β_4	0.2199	2.5111 **
Year (Y)	β_t	-0.0089	-2.0162 **
$(\text{Year})^2$	β_{tt}	-0.0006	-0.2940
(K2) x (Y)	β_{1t}	0.0563	
(L) x (Y)	β_{2t}	-0.0542	-3.2161 **
(FE) x (Y)	β_{3t}	0.0097	1.2012
(FT) x (Y)	β_{4t}	-0.0119	-0.7731
$(\text{K2})^2$	β_{11}	-1.5477	
(K2) x (L)	β_{12}	0.6062	
(K2) x (FE)	β_{13}	0.5972	
(K2) x (FT)	β_{14}	0.3443	
$(\text{L})^2$	β_{22}	0.2733	1.4912
(L) x (FE)	β_{23}	-0.4947	-3.6643 **
(L) x (FT)	β_{24}	-0.3847	-1.9342 *
$(\text{FE})^2$	β_{33}	0.2337	3.5140 **
(FE) x (FT)	β_{34}	-0.3362	-2.7600 **
$(\text{FT})^2$	β_{44}	0.3766	3.0166 **
Dummy for policy change	*Dpc*	-0.1094	-3.0324 **
Variance parameters			
Sigma	σ^2	0.0151	3.3863 **
Gamma	γ	0.4241	2.5029 **
Technical inefficiency effect	μ_i	Restricted to zero	
Time-varying inefficiency	η	0.2042	4.7590 ***

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Results for Model K9

Table A2.7 - Data for Waikato-Taranaki: Maximum likelihood estimates for parameters of the stochastic frontier for Model K9 under CRS (constant returns to scale), variables mean-differenced

Variables	Parameter	Coefficient	t-value
Stochastic Frontier			
Constant	β_0	5.7616	20.3629 ***
Cows (CW)	β_1	0.6021	
Labour (L)	β_2	0.1847	1.9626 *
Fertilizer (FT)	β_3	0.1019	2.7469 **
Capital (K9)	β_4	0.1112	2.6279 **
Year (Y)	β_t	0.0056	2.0439 **
Variance parameters			
Sigma	σ^2	0.0272	2.8179 **
Gamma	γ	0.7649	8.4709 ***
Technical inefficiency effect	μ_i	Restricted to zero	
Time varying inefficiency	η	Restricted to zero	

Note: *** - significant at 1% level (p<0.01)

** - significant at 5% level (p<0.05)

* - significant at 10% level (p<0.10)

Table A2.8 - Data for Canterbury-Southland: Maximum likelihood estimates for parameters of the stochastic frontier for Model K9 under CRS (constant returns to scale), variables mean-differenced

Variables	**Parameter**	**Coefficient**	**t-value**
Stochastic Frontier			
Constant	β_0	0.1176	2.0860 **
Cows (CW)	β_1	1.0456	
Labour (L)	β_2	0.0783	0.5860
Fertilizer (FT)	β_3	-0.0484	-0.8055
Capital (K9)	β_4	-0.0756	-1.0990
Year (Y)	β_t	0.0038	0.2277
$(\text{Year})^2$	β_{tt}	-0.0007	-0.5026
(CW) x (Y)	β_{1t}	-0.0511	
(L) x (Y)	β_{2t}	-0.0033	-0.1458
(FT) x (Y)	β_{3t}	0.0240	2.2061 **
(K9) x (Y)	β_{4t}	0.0304	2.3387 **
$(\text{CW})^2$	β_{11}	-0.7552	
(CW) x (L)	β_{12}	0.3667	
(CW) x (FT)	β_{13}	0.5447	
(CW) x (K9)	β_{14}	-0.1563	
$(\text{L})^2$	β_{22}	-0.1777	-0.4246
(L) x (FT)	β_{23}	-0.2745	-0.7390
(L) x (K9)	β_{24}	0.0856	0.2954
$(\text{FT})^2$	β_{33}	-0.2719	-2.2483
(FT) x (K9)	β_{34}	0.0018	0.0091
$(\text{K9})^2$	β_{44}	0.0689	0.5744
Variance parameters			
Sigma	σ^2	0.0186	2.3275 **
Gamma	γ	0.6250	3.8690 **
Technical inefficiency effect	μ_i	Restricted to zero	
Time varying inefficiency	η	0.0445	0.6234

Note: *** - significant at 1% level ($p<0.01$)

** - significant at 5% level ($p<0.05$)

* - significant at 10% level ($p<0.10$)

Appendix 3

Table A3.1- Data for Canterbury-Southland: farm technical efficiency estimates for all models

Model L8	all years
CS1	0,866
CS2	0,981
CS3	0,894
CS4	0,896
CS5	0,798
CS6	0,855
CS7	0,735
CS8	0,880
CS9	0,901
CS10	0,902
CS11	0,964
CS12	0,853
CS13	0,977
CS14	0,975
CS15	0,970
CS16	0,851

Note: Model L8 was time invariant. Hence, farms have the same efficiency over the entire period.

Model J7	1996/97	1997/98	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	2004/05	Geometric mean
CS1	0,774	0,812	0,844	0,872	0,894	0,913	0,929	0,942	0,953	0,880
CS2	0,953	0,962	0,969	0,975	0,979	0,983	0,986	0,989	0,991	0,976
CS3	0,811	0,844	0,871	0,894	0,913	0,929	0,942	0,952	0,961	0,901
CS4	0,541	0,607	0,667	0,720	0,765	0,805	0,838	0,867	0,890	0,735
CS5	0,813	0,845	0,872	0,895	0,914	0,929	0,942	0,953	0,961	0,901
CS6	0,798	0,833	0,862	0,886	0,907	0,923	0,937	0,949	0,958	0,893
CS7	0,451	0,524	0,592	0,653	0,708	0,755	0,796	0,831	0,861	0,672
CS8	0,720			0,838	0,866	0,890	0,910	0,926	0,939	0,867
CS9	0,894	0,913	0,929	0,942	0,952	0,961	0,968	0,974	0,979	0,945
CS10	0,747	0,789	0,825	0,855	0,881	0,902	0,920	0,934	0,946	0,864
CS11	0,821	0,852	0,878	0,900	0,918	0,933	0,945	0,955	0,963	0,906
CS12	0,602	0,662	0,715			0,836	0,864	0,888	0,908	0,774
CS13	0,897	0,916	0,931	0,943	0,954	0,962	0,969	0,975	0,980	0,947
CS14	0,967	0,973	0,978	0,982	0,986	0,988	0,990	0,992	0,994	0,984
CS15	0,857	0,882	0,903	0,920	0,935	0,947	0,956	0,964	0,971	0,925
CS16	0,798		0,861	0,886	0,906	0,923	0,937	0,949	0,958	0,901

Note: empty space when observation was missing, i.e., farm data were not collected

Model Y5	1996/97	1997/98	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	2004/05	Geometric mean
CS1	0,757	0,801	0,838	0,869	0,894	0,915	0,932	0,945	0,956	0,876
CS2	0,903	0,922	0,937	0,950	0,960	0,968	0,974	0,979	0,984	0,952
CS3	0,745	0,791	0,830	0,862	0,889	0,910	0,928	0,942	0,954	0,870
CS4	0,492	0,569	0,638	0,700	0,753	0,798	0,836	0,867	0,893	0,714
CS5	0,806	0,842	0,872	0,897	0,917	0,933	0,947	0,957	0,966	0,903
CS6	0,751	0,796	0,834	0,866	0,892	0,913	0,930	0,944	0,955	0,873
CS7	0,379	0,462	0,541	0,614	0,678	0,734	0,782	0,823	0,856	0,631
CS8	0,652			0,806	0,842	0,872	0,897	0,917	0,934	0,840
CS9	0,799	0,836	0,867	0,893	0,914	0,931	0,945	0,956	0,965	0,899
CS10	0,665	0,723	0,773	0,815	0,849	0,878	0,902	0,921	0,937	0,824
CS11	0,788	0,827	0,860	0,887	0,909	0,927	0,941	0,953	0,962	0,893
CS12	0,450	0,530	0,603			0,776	0,817	0,852	0,880	0,682
CS13	0,884	0,906	0,925	0,940	0,952	0,961	0,969	0,975	0,980	0,943
CS14	0,973	0,978	0,983	0,986	0,989	0,991	0,993	0,994	0,996	0,987
CS15	0,811	0,846	0,875	0,900	0,919	0,935	0,948	0,959	0,967	0,905
CS16	0,716		0,809	0,845	0,875	0,899	0,919	0,935	0,948	0,865

Note: empty space when observation was missing, i.e., farm data were not collected

Model K9	1996/97	1997/98	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	2004/05	Geometric mean
CS1	0,790	0,816	0,839	0,859	0,877	0,893	0,907	0,919	0,930	0,869
CS2	0,957	0,962	0,967	0,972	0,976	0,979	0,982	0,984	0,986	0,974
CS3	0,832	0,853	0,872	0,888	0,903	0,915	0,927	0,936	0,945	0,896
CS4	0,754	0,783	0,810	0,834	0,855	0,873	0,890	0,904	0,917	0,845
CS5	0,776	0,803	0,828	0,849	0,869	0,885	0,900	0,913	0,925	0,860
CS6	0,797	0,822	0,844	0,864	0,881	0,897	0,910	0,922	0,932	0,873
CS7	0,565	0,611	0,654	0,693	0,729	0,761	0,790	0,816	0,839	0,712
CS8	0,791			0,860	0,878	0,894	0,908	0,920	0,930	0,882
CS9	0,917	0,928	0,937	0,946	0,953	0,959	0,965	0,969	0,974	0,950
CS10	0,819	0,841	0,862	0,879	0,895	0,909	0,921	0,931	0,940	0,888
CS11	0,946	0,953	0,959	0,965	0,969	0,974	0,977	0,980	0,983	0,967
CS12	0,732	0,764	0,793			0,861	0,879	0,895	0,909	0,831
CS13	0,965	0,970	0,974	0,978	0,981	0,983	0,985	0,987	0,989	0,979
CS14	0,942	0,950	0,957	0,963	0,968	0,972	0,976	0,979	0,982	0,965
CS15	0,969	0,973	0,977	0,980	0,982	0,985	0,987	0,989	0,990	0,981
CS16	0,814		0,858	0,876	0,892	0,906	0,918	0,929	0,939	0,891

Note: empty space when observation was missing, i.e., farm data were not collected

Table A3.2- Data for Canterbury-Southland: farm technical efficiency change estimates for all models.

Model J7	1996/ 97	1997/ 98	1998/ 99	1999/ 00	2000/ 01	2001/ 02	2002/ 03	2003/ 04	2004/ 05	Geometric mean
CS1	1	1,0492	1,0398	1,0322	1,0261	1,0212	1,0172	1,0139	1,0113	1,0233
CS2	1	1,0089	1,0073	1,0059	1,0048	1,0039	1,0032	1,0026	1,0021	1,0043
CS3	1	1,0399	1,0323	1,0262	1,0213	1,0173	1,0140	1,0114	1,0092	1,0190
CS4	1	1,1224	1,0984	1,0792	1,0639	1,0516	1,0417	1,0337	1,0273	1,0570
CS5	1	1,0396	1,0321	1,0260	1,0211	1,0171	1,0139	1,0113	1,0092	1,0189
CS6	1	1,0431	1,0349	1,0283	1,0229	1,0186	1,0151	1,0122	1,0099	1,0205
CS7	1	1,1613	1,1291	1,1037	1,0834	1,0672	1,0542	1,0438	1,0354	1,0743
CS8	1				1,0337	1,0273	1,0221	1,0179	1,0146	1,0192
CS9	1	1,0211	1,0172	1,0139	1,0113	1,0092	1,0075	1,0061	1,0049	1,0101
CS10	1	1,0563	1,0455	1,0368	1,0298	1,0242	1,0196	1,0159	1,0129	1,0266
CS11	1	1,0375	1,0304	1,0247	1,0200	1,0162	1,0132	1,0107	1,0087	1,0179
CS12	1	1,1001	1,0806				1,0343	1,0278	1,0225	1,0437
CS13	1	1,0204	1,0166	1,0135	1,0110	1,0089	1,0072	1,0059	1,0048	1,0098
CS14	1	1,0062	1,0050	1,0041	1,0033	1,0027	1,0022	1,0018	1,0015	1,0030
CS15	1	1,0293	1,0238	1,0193	1,0157	1,0127	1,0103	1,0084	1,0068	1,0140
CS16	1			1,0284	1,0230	1,0187	1,0151	1,0123	1,0100	1,0153

Model Y5	1996/ 97	1997/ 98	1998/ 99	1999/ 00	2000/ 01	2001/ 02	2002/ 03	2003/ 04	2004/ 05	Geometric mean
CS1	1	1,0585	1,0464	1,0367	1,0291	1,0231	1,0184	1,0146	1,0116	1,0263
CS2	1	1,0210	1,0167	1,0133	1,0106	1,0084	1,0067	1,0053	1,0043	1,0096
CS3	1	1,0619	1,0490	1,0388	1,0308	1,0244	1,0194	1,0154	1,0122	1,0278
CS4	1	1,1562	1,1224	1,0962	1,0758	1,0599	1,0473	1,0375	1,0297	1,0685
CS5	1	1,0450	1,0357	1,0284	1,0225	1,0179	1,0142	1,0113	1,0090	1,0204
CS6	1	1,0602	1,0477	1,0378	1,0300	1,0238	1,0189	1,0150	1,0119	1,0271
CS7	1	1,2199	1,1713	1,1340	1,1052	1,0828	1,0653	1,0516	1,0408	1,0949
CS8	1				1,0451	1,0358	1,0283	1,0225	1,0178	1,0248
CS9	1	1,0469	1,0372	1,0295	1,0234	1,0186	1,0148	1,0117	1,0093	1,0212
CS10	1	1,0868	1,0685	1,0542	1,0429	1,0340	1,0269	1,0214	1,0169	1,0387
CS11	1	1,0499	1,0395	1,0314	1,0249	1,0198	1,0157	1,0125	1,0099	1,0225
CS12	1	1,1774	1,1388				1,0534	1,0422	1,0335	1,0724
CS13	1	1,0254	1,0202	1,0161	1,0128	1,0102	1,0081	1,0064	1,0051	1,0116
CS14	1	1,0057	1,0045	1,0036	1,0029	1,0023	1,0018	1,0014	1,0012	1,0026
CS15	1	1,0437	1,0347	1,0275	1,0219	1,0174	1,0138	1,0110	1,0087	1,0198
CS16	1			1,0441	1,0350	1,0277	1,0220	1,0175	1,0139	1,0228

Model K9	1996/ 97	1997/ 98	1998/ 99	1999/ 00	2000/ 01	2001/ 02	2002/ 03	2003/ 04	2004/ 05	Geometric mean
CS1	1	1,0328	1,0282	1,0243	1,0210	1,0181	1,0156	1,0134	1,0116	1,0183
CS2	1	1,0061	1,0052	1,0045	1,0039	1,0034	1,0029	1,0025	1,0022	1,0034
CS3	1	1,0255	1,0220	1,0190	1,0164	1,0141	1,0122	1,0105	1,0091	1,0143
CS4	1	1,0395	1,0340	1,0293	1,0252	1,0217	1,0187	1,0161	1,0139	1,0220
CS5	1	1,0354	1,0305	1,0263	1,0226	1,0195	1,0168	1,0145	1,0125	1,0197
CS6	1	1,0316	1,0272	1,0235	1,0202	1,0174	1,0150	1,0130	1,0112	1,0176
CS7	1	1,0814	1,0699	1,0600	1,0516	1,0444	1,0382	1,0328	1,0283	1,0449
CS8	1				1,0209	1,0180	1,0155	1,0134	1,0115	1,0132
CS9	1	1,0119	1,0103	1,0089	1,0077	1,0066	1,0057	1,0049	1,0043	1,0067
CS10	1	1,0277	1,0239	1,0206	1,0178	1,0153	1,0132	1,0114	1,0098	1,0155
CS11	1	1,0076	1,0066	1,0057	1,0049	1,0042	1,0037	1,0032	1,0027	1,0043
CS12	1	1,0436	1,0375				1,0207	1,0178	1,0154	1,0224
CS13	1	1,0048	1,0042	1,0036	1,0031	1,0027	1,0023	1,0020	1,0017	1,0027
CS14	1	1,0081	1,0070	1,0060	1,0052	1,0045	1,0039	1,0034	1,0029	1,0046
CS15	1	1,0043	1,0038	1,0032	1,0028	1,0024	1,0021	1,0018	1,0016	1,0024
CS16	1			1,0212	1,0183	1,0158	1,0136	1,0117	1,0101	1,0130

Table A3.3- Data for Canterbury-Southland: farm technical progress estimates for all models.

Model L8	1996/ 97	1997/ 98	1998/ 99	1999/ 00	2000/ 01	2001/ 02	2002/ 03	2003/ 04	2004/ 05	Geometric mean
CS1	1	1,0565	1,0455	1,0350	1,0392	1,0415	1,0334	1,0325	1,0292	1,0390
CS2	1	1,0326	1,0226	1,0270	1,0295	1,0264	1,0220	1,0332	1,0409	1,0293
CS3	1	1,0335	1,0301	1,0240	1,0271	1,0357	1,0452	1,0374	1,0279	1,0326
CS4	1	1,0530	1,0314	1,0096	1,0432	1,0454	1,0229	1,0292	1,0170	1,0314
CS5	1	1,0505	1,0557	1,0405	1,0171	1,0508	1,0689	1,0471	1,0360	1,0457
CS6	1	1,0226	1,0177	1,0153	1,0251	1,0270	1,0232	1,0171	1,0222	1,0213
CS7	1	1,0573	1,0651	1,0744	1,0664	1,0621	1,0662	1,0591	1,0482	1,0623
CS8	1			1,0401	1,0401	1,0379	1,0345	1,0267	1,0150	1,0323
CS9	1	1,0356	1,0170	0,9990	1,0162	1,0432	1,0396	1,0230	1,0152	1,0235
CS10	1	1,0280	1,0304	1,0310	1,0122	0,9957	0,9805	0,9631	0,9591	0,9996
CS11	1	1,0211	1,0258	1,0337	1,0322	1,0221	1,0155	1,0140	1,0078	1,0215
CS12	1	1,0498	1,0443			1,0232	1,0014	0,9900	0,9941	1,0169
CS13	1	1,0249	1,0212	1,0212	1,0124	1,0050	0,9965	0,9858	0,9884	1,0068
CS14	1	1,0205	1,0101	1,0160	1,0242	1,0161	1,0022	0,9911	0,9838	1,0079
CS15	1	1,0213	1,0168	1,0153	1,0315	1,0491	1,0436	1,0252	1,0149	1,0271
CS16	1		1,0341	1,0197	1,0084	1,0183	1,0264	1,0339	1,0316	1,0246

Model J7	1996/ 97	1997/ 98	1998/ 99	1999/ 00	2000/ 01	2001/ 02	2002/ 03	2003/ 04	2004/ 05	Geometric mean
CS1	1	0,9980	0,9971	0,9812	0,9791	0,9870	0,9946	0,9984	0,9928	0,9910
CS2	1	0,9710	0,9601	0,9659	0,9750	0,9856	0,9807	0,9815	0,9863	0,9757
CS3	1	0,9428	0,9690	0,9882	0,9852	0,9833	0,9831	0,9810	0,9901	0,9777
CS4	1	0,9545	0,9605	0,9633	0,9834	1,0128	1,0277	1,0374	1,0203	0,9945
CS5	1	0,9707	0,9919	1,0212	1,0197	1,0241	1,0119	0,9969	0,9933	1,0036
CS6	1	0,9641	0,9548	0,9572	0,9690	0,9742	0,9741	0,9618	0,9685	0,9654
CS7	1	0,9705	0,9691	0,9727	0,9896	1,0049	1,0074	1,0000	0,9915	0,9881
CS8	1			1,0130	1,0090	0,9960	0,9891	0,9887	0,9788	0,9957
CS9	1	0,9395	0,9368	0,9441	0,9562	0,9678	0,9644	0,9502	0,9482	0,9509
CS10	1	0,9638	0,9718	0,9702	0,9794	0,9831	0,9694	0,9653	0,9736	0,9721
CS11	1	0,9654	0,9683	0,9788	0,9726	0,9728	0,9840	0,9870	0,9874	0,9770
CS12	1	0,9386	0,9395			0,9587	0,9566	0,9596	0,9717	0,9540
CS13	1	0,9912	1,0040	0,9919	0,9709	0,9834	0,9956	0,9889	0,9783	0,9880
CS14	1	1,0056	1,0084	0,9995	0,9888	0,9708	0,9611	0,9745	0,9913	0,9874
CS15	1	0,9914	0,9885	0,9816	0,9893	1,0096	1,0072	0,9825	0,9651	0,9893
CS16	1		0,9491	0,9488	0,9419	0,9428	0,9482	0,9629	0,9723	0,9522

Model Y5	1996/ 97	1997/ 98	1998/ 99	1999/ 00	2000/ 01	2001/ 02	2002/ 03	2003/ 04	2004/ 05	Geometric mean
CS1	1	1,0111	1,0067	0,9922	0,9915	0,9979	1,0008	1,0031	1,0002	1,0004
CS2	1	0,9805	0,9717	0,9785	0,9867	0,9889	0,9801	0,9877	0,9984	0,9840
CS3	1	0,9696	0,9870	0,9971	0,9937	0,9953	1,0034	1,0004	1,0045	0,9938
CS4	1	0,9815	0,9808	0,9836	1,0040	1,0160	1,0187	1,0325	1,0216	1,0047
CS5	1	0,9767	0,9935	1,0174	1,0135	1,0245	1,0217	1,0073	1,0033	1,0071
CS6	1	0,9724	0,9669	0,9707	0,9829	0,9871	0,9889	0,9785	0,9802	0,9784
CS7	1	0,9821	0,9876	0,9986	1,0107	1,0153	1,0178	1,0118	1,0063	1,0037
CS8	1			1,0273	1,0182	1,0018	0,9934	0,9928	0,9876	1,0034
CS9	1	0,9633	0,9585	0,9581	0,9668	0,9797	0,9815	0,9710	0,9664	0,9681
CS10	1	0,9742	0,9831	0,9922	0,9955	0,9954	0,9847	0,9806	0,9851	0,9863
CS11	1	0,9761	0,9813	0,9894	0,9882	0,9887	0,9937	0,9947	0,9932	0,9881
CS12	1	0,9633	0,9627			0,9753	0,9740	0,9747	0,9809	0,9718
CS13	1	0,9967	1,0100	0,9987	0,9738	0,9871	1,0041	0,9965	0,9861	0,9941
CS14	1	1,0060	1,0047	1,0012	1,0001	0,9861	0,9764	0,9853	0,9949	0,9943
CS15	1	0,9936	0,9928	0,9918	1,0037	1,0265	1,0226	0,9991	0,9861	1,0019
CS16	1		0,9663	0,9739	0,9730	0,9735	0,9788	0,9883	0,9936	0,9782

Model K9	1996/ 97	1997/ 98	1998/ 99	1999/ 00	2000/ 01	2001/ 02	2002/ 03	2003/ 04	2004/ 05	Geometric mean
CS1	1	1,0028	1,0114	1,0025	1,0054	1,0160	1,0248	1,0213	1,0141	1,0122
CS2	1	0,9975	0,9936	0,9972	1,0029	1,0165	1,0202	1,0186	1,0216	1,0084
CS3	1	0,9731	0,9882	0,9970	1,0013	1,0049	1,0047	1,0042	1,0085	0,9977
CS4	1	0,9969	1,0095	1,0023	1,0117	1,0270	1,0266	1,0253	1,0146	1,0142
CS5	1	1,0083	1,0159	1,0225	1,0229	1,0326	1,0269	1,0124	1,0130	1,0193
CS6	1	0,9863	0,9840	0,9803	0,9892	0,9985	0,9973	0,9941	1,0060	0,9919
CS7	1	1,0153	1,0050	0,9981	1,0005	1,0132	1,0197	1,0175	1,0079	1,0096
CS8	1			0,9833	1,0025	1,0231	1,0259	1,0200	1,0078	1,0103
CS9	1	0,9908	0,9947	0,9997	1,0115	1,0233	1,0168	1,0077	0,9986	1,0053
CS10	1	0,9985	0,9943	0,9817	0,9860	0,9827	0,9624	0,9659	0,9783	0,9812
CS11	1	0,9953	0,9987	1,0092	1,0027	1,0027	1,0051	0,9998	1,0029	1,0020
CS12	1	0,9858	0,9863			0,9973	0,9930	0,9957	1,0044	0,9937
CS13	1	1,0152	1,0255	1,0165	1,0161	1,0148	1,0023	0,9976	0,9951	1,0103
CS14	1	0,9975	1,0066	1,0042	0,9955	0,9936	0,9940	0,9995	1,0078	0,9998
CS15	1	1,0082	1,0062	0,9941	0,9947	1,0057	1,0069	0,9998	0,9966	1,0015
CS16	1		0,9977	0,9691	0,9527	0,9687	0,9788	0,9949	1,0015	0,9803

Table A3.4- Data for Canterbury-Southland: farm total factor productivity estimates for all models.

Model L8	1996/ 97	1997/ 98	1998/ 99	1999/ 00	2000/ 01	2001/ 02	2002/ 03	2003/ 04	2004/ 05	Geometric mean
CS1	1	1,0565	1,0455	1,0350	1,0392	1,0415	1,0334	1,0325	1,0292	1,0390
CS2	1	1,0326	1,0226	1,0270	1,0295	1,0264	1,0220	1,0332	1,0409	1,0293
CS3	1	1,0335	1,0301	1,0240	1,0271	1,0357	1,0452	1,0374	1,0279	1,0326
CS4	1	1,0530	1,0314	1,0096	1,0432	1,0454	1,0229	1,0292	1,0170	1,0314
CS5	1	1,0505	1,0557	1,0405	1,0171	1,0508	1,0689	1,0471	1,0360	1,0457
CS6	1	1,0226	1,0177	1,0153	1,0251	1,0270	1,0232	1,0171	1,0222	1,0213
CS7	1	1,0573	1,0651	1,0744	1,0664	1,0621	1,0662	1,0591	1,0482	1,0623
CS8	1			1,0401	1,0401	1,0379	1,0345	1,0267	1,0150	1,0323
CS9	1	1,0356	1,0170	0,9990	1,0162	1,0432	1,0396	1,0230	1,0152	1,0235
CS10	1	1,0280	1,0304	1,0310	1,0122	0,9957	0,9805	0,9631	0,9591	0,9996
CS11	1	1,0211	1,0258	1,0337	1,0322	1,0221	1,0155	1,0140	1,0078	1,0215
CS12	1	1,0498	1,0443			1,0232	1,0014	0,9900	0,9941	1,0169
CS13	1	1,0249	1,0212	1,0212	1,0124	1,0050	0,9965	0,9858	0,9884	1,0068
CS14	1	1,0205	1,0101	1,0160	1,0242	1,0161	1,0022	0,9911	0,9838	1,0079
CS15	1	1,0213	1,0168	1,0153	1,0315	1,0491	1,0436	1,0252	1,0149	1,0271
CS16	1		1,0341	1,0197	1,0084	1,0183	1,0264	1,0339	1,0316	1,0246

Model J7	1996/ 97	1997/ 98	1998/ 99	1999/ 00	2000/ 01	2001/ 02	2002/ 03	2003/ 04	2004/ 05	Geometric mean
CS1	1	1,0470	1,0368	1,0128	1,0047	1,0079	1,0116	1,0123	1,0040	1,0170
CS2	1	0,9797	0,9671	0,9716	0,9797	0,9894	0,9838	0,9841	0,9884	0,9804
CS3	1	0,9805	1,0003	1,0141	1,0062	1,0003	0,9969	0,9921	0,9992	0,9987
CS4	1	1,0713	1,0550	1,0396	1,0462	1,0650	1,0705	1,0723	1,0481	1,0584
CS5	1	1,0092	1,0237	1,0478	1,0412	1,0416	1,0260	1,0081	1,0024	1,0249
CS6	1	1,0057	0,9882	0,9843	0,9912	0,9923	0,9888	0,9735	0,9781	0,9877
CS7	1	1,1270	1,0943	1,0736	1,0722	1,0724	1,0621	1,0438	1,0266	1,0711
CS8	1				1,0430	1,0232	1,0110	1,0065	0,9930	1,0152
CS9	1	0,9593	0,9529	0,9573	0,9671	0,9768	0,9716	0,9560	0,9529	0,9617
CS10	1	1,0181	1,0161	1,0060	1,0086	1,0069	0,9884	0,9806	0,9861	1,0012
CS11	1	1,0016	0,9977	1,0029	0,9921	0,9886	0,9969	0,9976	0,9959	0,9967
CS12	1	1,0326	1,0152				0,9895	0,9862	0,9936	1,0033
CS13	1	1,0114	1,0206	1,0053	0,9815	0,9921	1,0028	0,9947	0,9830	0,9989
CS14	1	1,0119	1,0135	1,0036	0,9921	0,9735	0,9632	0,9763	0,9927	0,9907
CS15	1	1,0205	1,0121	1,0005	1,0048	1,0225	1,0177	0,9907	0,9717	1,0049
CS16	1			0,9757	0,9636	0,9604	0,9625	0,9747	0,9819	0,9698

Model Y5	1996/97	1997/98	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	2004/05	Geometric mean
CS1	1	1,0703	1,0534	1,0287	1,0203	1,0210	1,0191	1,0177	1,0118	1,0301
CS2	1	1,0011	0,9880	0,9916	0,9971	0,9972	0,9867	0,9930	1,0026	0,9946
CS3	1	1,0296	1,0353	1,0358	1,0243	1,0196	1,0229	1,0158	1,0167	1,0250
CS4	1	1,1349	1,1009	1,0783	1,0801	1,0768	1,0669	1,0711	1,0520	1,0824
CS5	1	1,0207	1,0290	1,0463	1,0363	1,0428	1,0362	1,0187	1,0123	1,0302
CS6	1	1,0309	1,0130	1,0074	1,0123	1,0105	1,0076	0,9931	0,9919	1,0083
CS7	1	1,1980	1,1567	1,1324	1,1171	1,0994	1,0843	1,0640	1,0473	1,1114
CS8	1				1,0641	1,0377	1,0216	1,0152	1,0052	1,0285
CS9	1	1,0085	0,9941	0,9864	0,9895	0,9979	0,9960	0,9824	0,9754	0,9912
CS10	1	1,0588	1,0505	1,0459	1,0382	1,0292	1,0112	1,0015	1,0018	1,0294
CS11	1	1,0248	1,0201	1,0204	1,0128	1,0083	1,0093	1,0071	1,0030	1,0132
CS12	1	1,1342	1,0963				1,0260	1,0159	1,0137	1,0561
CS13	1	1,0220	1,0304	1,0148	0,9863	0,9971	1,0122	1,0030	0,9912	1,0070
CS14	1	1,0117	1,0092	1,0048	1,0030	0,9883	0,9781	0,9867	0,9961	0,9972
CS15	1	1,0371	1,0272	1,0191	1,0257	1,0443	1,0367	1,0100	0,9947	1,0242
CS16	1			1,0169	1,0071	1,0005	1,0003	1,0055	1,0074	1,0063

Model K9	1996/97	1997/98	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	2004/05	Geometric mean
CS1	1	1,0357	1,0399	1,0269	1,0265	1,0343	1,0408	1,0350	1,0258	1,0331
CS2	1	1,0035	0,9988	1,0017	1,0068	1,0199	1,0232	1,0211	1,0239	1,0123
CS3	1	0,9979	1,0099	1,0159	1,0177	1,0191	1,0169	1,0148	1,0176	1,0137
CS4	1	1,0362	1,0438	1,0317	1,0373	1,0494	1,0458	1,0419	1,0287	1,0393
CS5	1	1,0440	1,0469	1,0494	1,0461	1,0527	1,0442	1,0271	1,0256	1,0419
CS6	1	1,0175	1,0108	1,0033	1,0092	1,0160	1,0123	1,0070	1,0173	1,0116
CS7	1	1,0979	1,0752	1,0580	1,0521	1,0581	1,0586	1,0509	1,0364	1,0608
CS8	1				1,0234	1,0415	1,0419	1,0337	1,0195	1,0320
CS9	1	1,0026	1,0049	1,0086	1,0192	1,0301	1,0226	1,0126	1,0028	1,0129
CS10	1	1,0261	1,0181	1,0019	1,0035	0,9977	0,9751	0,9769	0,9879	0,9983
CS11	1	1,0029	1,0053	1,0149	1,0076	1,0070	1,0088	1,0029	1,0056	1,0069
CS12	1	1,0287	1,0233				1,0135	1,0134	1,0199	1,0198
CS13	1	1,0200	1,0298	1,0202	1,0193	1,0175	1,0046	0,9996	0,9969	1,0134
CS14	1	1,0056	1,0136	1,0102	1,0007	0,9981	0,9979	1,0028	1,0108	1,0050
CS15	1	1,0126	1,0100	0,9973	0,9975	1,0082	1,0090	1,0016	0,9981	1,0043
CS16	1			0,9897	0,9701	0,9840	0,9921	1,0066	1,0116	0,9923

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